DISASTER RISKS, SOCIAL PREFERENCES, AND POLICY EFFECTS

FIELD EXPERIMENTS IN SELECTED ASEAN AND EAST ASIAN COUNTRIES

Edited by

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Acknowledgements

This report consists of the papers from ERIA's research project on "Disaster Risks, Social Preferences, and Policy Effects: Field Experiment Studies in Selected East Asia" in Fiscal Year 2013-14. It aims to produce the academic foundations of the nexus between a disaster and individual/social preferences so that we can fill in the remaining large gap in the literature on behavioural impacts of disasters in East Asia.

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List of Abbreviation

AI	Asian Influenza
AMSs	ASEAN Member States
ANOVA	Analysis of Variance
ASEAN	Association of Southeast Asian Nations
BAAC	Bank of Agriculture and Agricultural Cooperatives
CDF	Cumulative Distribution Function
CRED	Centre for Research on the Epidemiology of Disasters
CRRA	constant relative risk aversion
CTB	Convex Time Budget
DMPL	Double Multiple Price List
EM-DAT	Emergency Events Database
ERIA	Economic Research Institute for ASEAN and East Asia
FE	Fixed effect
GDP	gross domestic product
GSS	General Social Survey
ICC	Interclass correlation coefficient
IRRI	International Rice Research Institute
IRSS	Indian Remote Sensing Satellite
ITT	intent-to-treat
JPY	Japan Yen
MPL	Multiple Price List
NASA-MODIS	National Aeronautics and Space Administration - Moderate Resolution Imaging Spectroradiometer
NCPO	National Council for Peace and Order
NGO	non-governmental organisations
NLS	non-linear least squares
OLS	ordinary least squares
PTSD	post-traumatic stress disorder
RIETI	Research Institute of Economy, Trade and Industry
SDQ	Strengths and Difficulties Questionnaire
UCL	University Colleague London
USD	United States Dollar

VHLSS	Viet Nam Household Living Standards Survey
VND	Vietnam Dollar
WFP	World Food Program

Executive Summary

While the Asian countries have been successful in achieving economic growth and poverty reduction, the region cannot avoid exposure to a variety of disasters. Indeed, Asia, particularly the area of the ASEAN Member States (AMSs), is the most prone region to disasters in the world.

In preparation for or the aftermath of a disaster, a variety of market and non-market mechanisms are indispensable for people to maintain their livelihood. Market insurance mechanisms include mechanisms through direct insurance markets as well as indirect mechanisms based on credit, labor, and other market transactions.

Since market insurance mechanisms are still weak, especially against damage caused by disasters, governments and communities can play important roles in strengthening overall insurance mechanisms. The state can provide public insurance schemes and social protection programmes. Community-based informal insurance mechanisms can also make up for a lack of formal insurance schemes. Such informal insurance networks themselves comprise the important component of social capital in a broader sense.

To strengthen market, state, and community insurance mechanisms, we need to have a strong grasp of the roles of individual and social preferences. By employing combined data sets, we identify effective policies to facilitate livelihood recovery of the victims of a disaster, considering closely people's behavioural responses against unexpected events caused by a variety of natural and man-made disasters.

In this project, our first aim is to produce the academic foundations of the nexus between a disaster and individual/social preferences so that we can fill in the remaining large gap in the literature on behavioural impacts of disasters by investigating two issues: first, whether and how a disaster affects preferences; and second, how preferences determine the vulnerability and resilience against damage caused by a disaster.

We believe that such a study is also indispensable in terms of designing and implementing appropriate post-disaster policies. To achieve this aim, we employ both existing data and new experiments from selected fields to quantify heterogeneous behavioural impacts of the disaster. Through this project, we can provide important policy implications for better insurance mechanisms at community, national, and regional level, generating inputs for high-level forums of the Association of Southeast Asian Nations (ASEAN) and East Asia.

In order to approach the first issue, whether and how a disaster affects preferences, it is indispensable to grasp people's individual and social preferences correctly by carrying out carefully designed experiments. Canonical methods as well as a new experiment such as the "Convex Time Budget (CTB)" experiment were conducted in selected sites to elicit and compare social preferences in different Asian countries and areas.

To carry out an assessment of the second issue, how preferences determine vulnerability and resilience, we employ standard and non-standard outcome measures in economics. Our outcome evaluation criteria include: standard individual decisions, particularly consumption and saving decisions based on the standard Euler equation, firm decisions and performance, psychosocial outcomes, and human capital outcomes. Basically, in each component, data on welfare measures such as consumption, ex post risk coping strategy against a disaster, and other dimensions such as social networks were collected and analysed by using multi-purpose household survey instruments together with the carefully designed experiments. Also, we employ relatively new measures in economics such as management practices and psychosocial measures as outcome measures. The latter measure is to capture post-traumatic stress disorder (PTSD), which has been studied extensively in public health and social epidemiology literature.

There are several policy implications from the findings of our research project.

First, the poor might be significantly risk averse and present-biased as in the case of farmers in the Philippines, Thailand, Viet Nam, and Cambodia. Natural disasters make the poor more present-biased and risk averse than those who are unaffected by disasters. AlsoAccordingly, disasters seem to undermine weaken the effectiveness of the pre-existing informal network of social safety nets. Such impacts of disasters may stimulate people's too much dependence on financial and non-financial assistance from the government, donor agencies, and NGOs, undermining sound post-disaster reconstruction or "building back better." Reinforced present-bias may induce substantial procrastination behaviors such as over-eating, over-spending, drinking, smoking, gambling, and over-indebtedness. Risk aversion would also facilitate procrastination behaviors. Since careless cash and in-kind transfers to the victims will worsen procrastination behaviors, the government and donor agencies should carefully design incentive-compatible safety net and development interventions to establish "commitments" against procrastination behaviors. Examples may include carefully-designed in-kind or voucher transfers rather than pure cash transfers, disaster loan programs, and commitment micro-saving programs.

Second, the importance of individual preferences can be also found in business investments. As found in the case of Lao PDR, firms with risk adverse managers are more likely to self-finance investments rather than to employ borrowing from a bank or other informal sources, leading to lower overall asset level. A risk averse firm manger is more likely to face binding "self-inflicted" borrowing constraints on additional investments. Risk tolerant managers, are more likely to have adopted better practices and to achieve employment stability. To facilitate "resilient" firm investments, it will be indispensable to make managers take risks (promoting entrepreneurship) by providing effective insurance mechanisms against business related risks. Concrete examples may include business information sharing network, credit guarantee system, and public facilitation of trade credit.

Third, natural disasters generate not only economic damages but also serious psychosocial and family problems as shown in the case of the Great Sichuan Earthquake in China and preschool children's psychological health in Fukushima. Such negative impacts seem to be large substantial among children and teenagers who are in an important phase of accumulating their human capital. Since non-cognitive skills may be more malleable than cognitive skills at later ages, the government must play an important role in facilitating human capital accumulation of the young who are affected natural disasters in a broader sense effectively by amending not only cognitive skills at school but also the non-cognitive skills of the victimized children and teenagers directly or indirectly. In addition to rehabilitation of infrastructure and reconstruction of family and community economies, special cares and resources should be provided at schools and out of schools to amend psychosocial damages caused on the students. Carefully-designed "rehabilitation camps" for the affected children may also be effective to weather the problems.

In sum, it would be imperative to strengthen market, state, and community insurance mechanisms by promoting risk control and financing instruments such as "hard" insurance schemes within each country and across countries in the region. Yet, we also need to place special care on subtle psychosocial and behavioral problems of the victimized children, teenagers, business managers, and other ordinal people.

CHAPTER 1
Disaster Risks, Social Preferences, and Policy Effects: Field Experiments in Selected ASEAN and East Asian Countries

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1. Introduction

Recently, a number of major natural disasters have hit both developed and developing countries. Disasters can have serious negative effects, not only in terms of loss of lives, but also on the livelihoods of survivors in the aftermath of the disaster. In Asia, a series of recent devastating disasters include the 2013 Typhoon Haiyan (Yolanda) in the Philippines, the 3/11 compound disasters in Tohoku, Japan in 2011, the 2008 Sichuan earthquake in China, and the massive floods in Thailand in 2011. The tsunami disaster in Tohoku was accompanied by a serious technological disaster involving the leaking of radioactive matter from a nuclear power plant. Global economies have been impaired by global financial crises such as the Latin American debt crisis in the 1980s, the Asian financial crisis of the late 1990s and the global financial crisis triggered by the 2008 Lehman Shock. Nations in Africa are still at war and involved in conflicts, and terrorist attacks are having serious impacts even on advanced nations. These natural and manmade disasters show distinct trends across the globe: Natural and technological disasters have been increasing more rapidly in frequency, in terms of the average occurrence of disaster per country per year, than financial crises and violence-related disasters (Cavallo and Noy, 2009;

Kellenberg and Mobarak, 2011; Strömberg, 2007).

Disasters can be subdivided into four major groups (Sawada, 2007). Natural disasters comprise the first category, which includes hydrological disasters (floods), meteorological disasters (storms or typhoons), climatological disasters (droughts), geophysical disasters (earthquakes, tsunamis and volcanic eruptions), and biological disasters (epidemics and insect infestations). The second type of disaster revolves around technological disasters, i.e., industrial accidents (chemical and oil spills, nuclear power plant meltdowns, industrial infrastructure collapse) and transport accidents (air, rail, road or water transport). The final two disaster types involve manmade disasters, which include economic crises (hyperinflation, banking crises and currency crises) and violence-related disasters (terrorism, civil strife, riots, and civil and external wars). As Aldrich, Sawada and Oum (2014) showed, while natural and technological disasters have been rapidly increasing, the occurrence of financial crises and war have maintained stable patterns over time.

While the Asian countries have been successful in achieving economic growth and poverty reduction, the region cannot avoid being greatly exposed to a variety of disasters. Indeed, Asia, particularly the area of the Association of Southeast Asian Nations (ASEAN) Member States (AMSs), is the region most prone to disasters in the world (Sawada and Zen, 2014). Natural disasters in particular have been increasing in Asia.

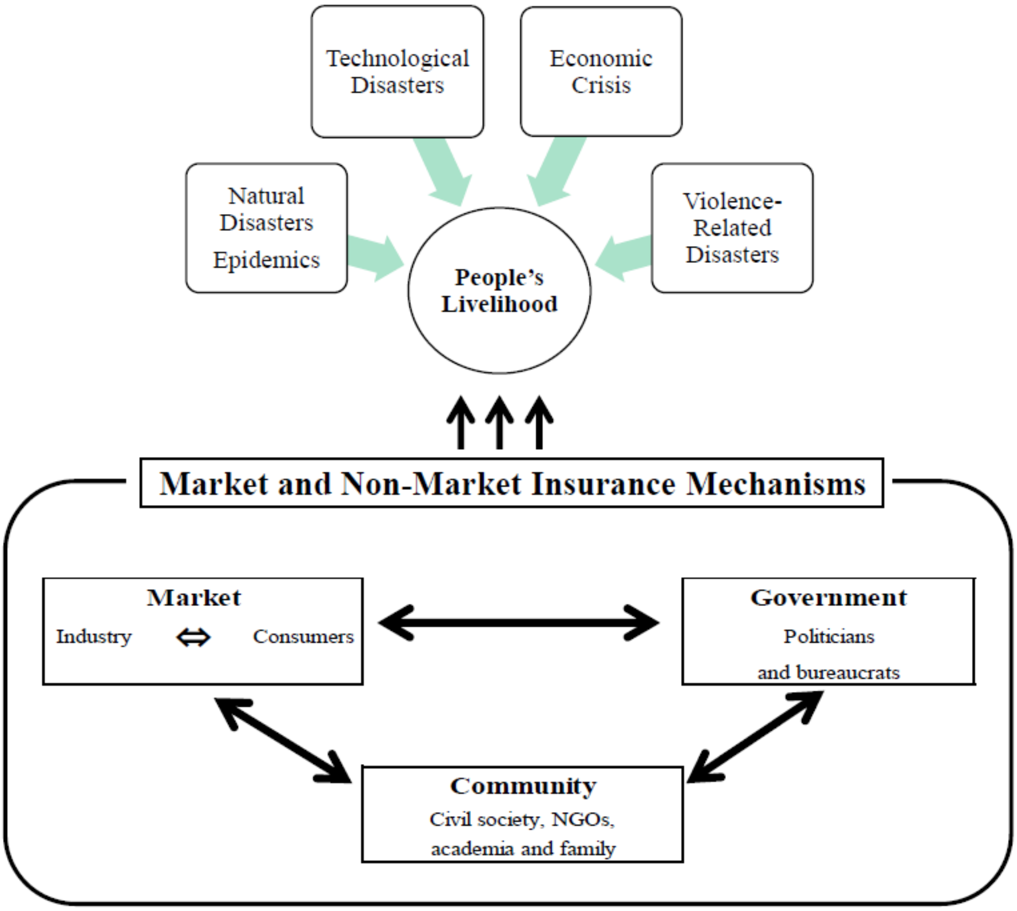
2. Market, State, and Community Insurance Mechanisms

To prepare for disasters and their aftermath, a variety of market and non-market mechanisms are indispensable for minimising loss of life when disaster strikes and for people to maintain their livelihood in the aftermath of a disaster. To illustrate such mechanisms, we adopt the framework of community, market, and state in the economic system of Hayami (2009), as seen below in Figure 1.1 (Aldrich, *et al.*, 2014).

The market serves as the mechanism that coordinates profit-seeking individuals and firms through competition using price signals. Naturally, the market has an advantage in matching the demand and supply of private tradable goods. Potentially, risks can be traded in credit and insurance markets, but it is often difficult to trade risks of disasters that are characterised by rare and unforeseen events. Hence, insurance market mechanisms are incomplete at best in trading disaster risks. This is a typical case of market failure. When markets fail, the government works as the institution that forces people to adjust their resource allocations by regulation or fiat so that resource misallocation due to market failure can be corrected. Typically, the government plays an important role in supplying global or pure public goods that private firms may be reluctant to provide. A public insurance mechanism for disasters is an example of such public goods. Disaster risks can be diversified away through governmental tax and expenditure mechanisms as well as other intertemporal resource smoothing mechanisms through the government's budget. In sum, market and government mechanisms play mutually complementary roles when markets are not functioning well against disasters. Yet, the government may also fail due to misbehaviour of selfish politicians and bureaucrats who seek to maximise their own benefits. To fill the gap in resource misallocation arising from market and government failures, community enforcement mechanisms based on social capital also play an indispensable role. A local community guides residents and members to work voluntarily and collectively based on historical social interactions and norms. The community facilitates the supply of local public goods, enforces informal transactions, and preserves reciprocal social safety nets. In the aftermath of a disaster, the community's mutual insurance as well as the family's self-insurance mechanisms can amend a lack of effective market and government insurance mechanisms.[1] Hence, the complementarity among market, government, and community is key to a successful disaster management and reconstruction system.

[1] There have been plenty of studies on consumption insurance in developing countries. See, for example, Townsend (1994), and Ligon (2008). Kohara, *et al*. (2008) and Sawada and Shimizutani (2007) applied the framework to test the validity of overall insurance mechanisms against damage caused by the Great Hanshin-Awaji (Kobe) earthquake.

Figure 1.1: Market, State, and Community Insurance Mechanisms



Source: Aldrich, *et al.* (2014) based on Hayami (2009).

2.1. Market Mechanisms

Market insurance mechanisms include mechanisms through direct insurance markets as well as indirect mechanisms based on credit, labour, and other market transactions. Direct market-based insurance can be classified into two types: indemnity-based insurance and index-based insurance. Examples of the former insurance are crop insurance, health insurance, and earthquake insurance. The latter insurance products include micro-insurance or weather insurance such as rainfall index insurance, temperature insurance, area-based index insurance.

According to Table 1.1, during the past decade, Asia experienced more than 150 natural disasters annually (40% of the world total), affecting more than 200 million people annually (about 90% of the world total) and causing more than USD 41.6 billion in annual damage (39%). Yet, Munic Re's 2010

NatCatSERVICE data reports that only 9% of total property losses due to natural disasters in Asia was covered by private insurance, compared with about USD 9 billion of the USD 12 billion (75%) in total property losses that was covered by private insurance in the case of the 2011 Christchurch, New Zealand earthquake.

Table 1.1: Natural Disaster Occurrence and Impacts by Region (Annual Average Figures between 2001 and 2010)

(1) Number of Natural Disasters

	Africa	Americas	Asia	Europe	Oceania	Global
Climatological	9	12	11	17	1	50
Geophysical	3	7	21	2	2	35
Hydrological	44	39	82	24	6	195
Meteorological	9	34	40	14	7	104
Total	65	92	153	58	16	384

Data: Annual Disaster Statistical Review 2011, CRED, IRSS & UCL, 2012.

(2) Number of Victims (in millions)

	Africa	Americas	Asia	Europe	Oceania	Global
Climatological	12.29	1.22	63.45	0.27	0.00	77.23
Geophysical	0.08	1.02	7.77	0.01	0.04	8.92
Hydrological	2.18	3.31	100.82	0.35	0.04	106.70
Meteorological	0.35	2.72	35.88	0.11	0.04	39.10
Total	14.91	8.27	207.92	0.74	0.12	231.95

Data: Annual Disaster Statistical Review 2011, CRED, IRSS & UCL, 2012.

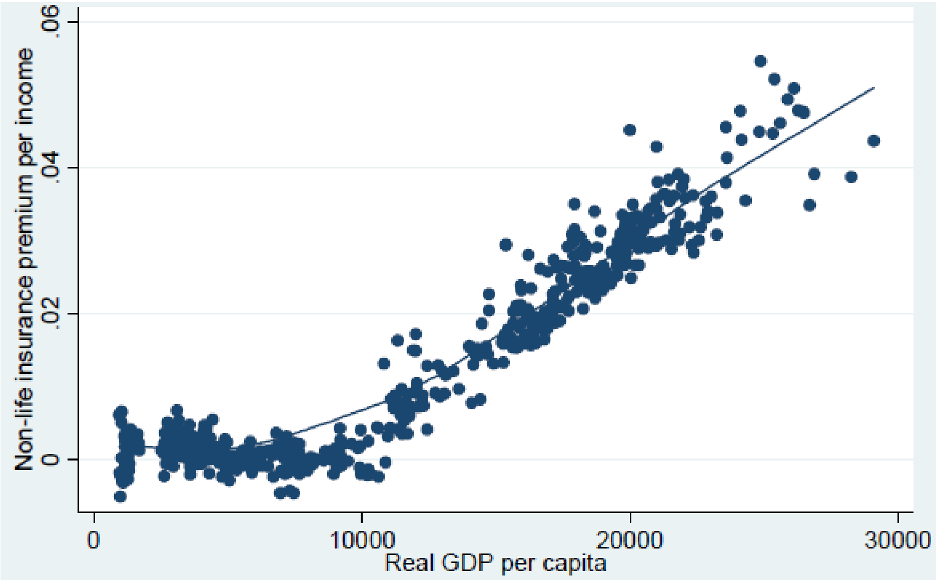
(3) Damage (in Billion USD)

	Africa	Americas	Asia	Europe	Oceania	Global
Climatological	0.04	1.90	3.45	3.23	0.48	9.10
Geophysical	0.69	4.75	17.38	0.57	0.69	24.08
Hydrological	0.28	3.15	11.15	5.57	1.24	21.39
Meteorological	0.08	40.47	9.62	4.03	0.56	54.77
Total	1.10	50.27	41.61	13.40	2.97	109.35

Data: Annual Disaster Statistical Review 2011, CRED, IRSS & UCL, 2012.

In fact, cross-country data uncovers the limitation of general insurance mechanisms especially in developing countries (Outreville, 1990; Enz, 2000). According to Figure 1.2, there is a positive relationship between volume of life and non-life premiums per capita and gross domestic product (GDP) per capita. Moreover, it is evident that the fitted slope will be larger than unity. This suggests that formal insurance appears to be a luxury, especially in low- and middle-income countries and that people's preferences are characterised by increasing risk aversion.[2]

Figure 1.2: Cross-Country Income Elasticity for Life and Non-life Formal Insurance Demand



Source: Nakata and Sawada (2009).

Traditional indemnity-based insurance has been suffering from the classical problems of moral hazard, adverse selection, and high transaction costs. Moral hazard is a problem in that being insured raises the probability of losses. The problem of adverse selection is that, for example, those farmers taking the greatest risks or unhealthy individuals are most eager to purchase insurance, undermining fair insurance schemes. Finally, transactions costs are significant because large numbers of small payments need to be made based on damage

[2] However, provided that the poor have higher potential demand for insurance because their marginal utility loss from a downside risk is higher than for the rich, demand for informal insurance instruments is expected to be higher in developing countries. In response to the macro-micro paradox in demand for insurance, Nakata and Sawada (2009) employed wealth data rather than income data to estimate insurance demand elasticity more precisely.

assessed by insurers on an individual basis.

To mitigate such problems, index insurance contracts have been attracting widespread attention (Hazell, 2003; Morduch, 2006; Skees, *et al.*, 2005; Gine and Yang, 2009; Cole, *et al.*, 2013; Clarke and Grenham, 2013). Index insurance contracts are drawn up against specific events such as droughts or floods, defined and recorded at the regional level. As such, index insurance contracts have a number of benefits: they can cover aggregate events; they are affordable and accessible even to the poor; they are easy to implement and privately managed; and they are free from moral hazard, adverse selection and the high transaction costs involved in traditional agricultural insurance contracts such as crop insurance schemes. The World Bank and other institutions have been piloting weather-based index insurance contracts in Morocco, Mongolia, Peru, Viet Nam, Ethiopia, Guatemala, India, Mexico, Nicaragua, Romania and Tunisia. Since natural disasters are typically aggregate events, index insurance is thought to be an appropriate instrument to combat them.

And yet, take-up of rainfall insurance, which is the most popular index insurance, has remained surprisingly low (Gine and Yang, 2009; Cole, *et al*., 2013; Dercon, *et al*., 2014; Clarke and Grenham, 2013). Indeed, designing index type insurance against natural disasters faces three major constraints. First, natural disasters are typically rare events, which makes it difficult to design actuarially fair insurance. Since obtaining historical data on natural disaster patterns is hard, it is almost impossible to set appropriate premiums for insurance (Morduch, 2004). Secondly, related to the first issue, even if appropriate premiums are set, the poor, who potentially should demand insurance against natural disasters may find it difficult to recognise the value of index type insurance against natural disasters or may not be able to purchase such insurance due to financial constraints. This may be an inevitable consequence because natural disasters are often characterised by unforeseen contingencies by nature and because the poor are often myopic with high time discount rates (Pender, 1996). There may also be a lack of trust toward insurance suppliers. Moreover, the existence of "basis risk", with which an individual could incur damage he/she cannot be sufficiently compensated for, will also constrain demand for index insurance. This problem has been identified as an inevitable drawback of index insurance because index contracts essentially trade off basis risk for transaction costs (Morduch, 2004; Hazell, 2003). Finally, natural disasters are highly covariate risks which often cannot be diversified within a country. Accordingly, insurers may need to secure their financial position by using international reinsurance markets, but reinsurance markets and trades of catastrophe (CAT) bonds are still less developed with limited capacity. Also, as an indication of the overall effectiveness of mutual insurance across national borders, recent studies show that the extent of international risk sharing remains surprisingly small (Obstfed and Rogoff, 2001; Lewis, 1996). Using data on hurricane exposure, Yang (2008) found that the poor's hurricane exposure leads to a substantial increase in migrants' remittances, so that total financial inflows from all sources in the three years following hurricane exposure amount to roughly three-fourths of estimated damage. This suggests that aggregated shock arising from natural disasters can be insured against at least partially depending on income level and the nature of the disasters.

2.2. Non-Market Insurance Mechanisms

Since market insurance mechanisms are still weak, especially against damage caused by disasters, governments and communities can play important roles in strengthening overall insurance mechanisms. The state can provide public insurance schemes and social protection programmes. Examples of public insurance programmes include: publicly provided health and other insurance programmes, subsidisation of private insurance, provision of public re-insurance schemes such as the earthquake re-insurance mechanism in Japan, food aid programmes for disaster-affected people, cash and in-kind transfers to victims, and targeted free social service provisions such as free primary health care.

Community-based informal insurance mechanisms can also make up for a lack of formal insurance schemes. Such mechanisms are achieved by mutual informal reciprocal transfers and credit provision among relatives, friends, and neighbours. Such informal insurance networks themselves comprise the important component of social capital in a broader sense. In fact, several studies found that in East and Southeast Asia many households are likely to be altruistically linked through a widespread and operative informal transfer network. As amounts of public transfers increase, donors of altruistically linked private transfers cut back their private transfer provisions. A government subsidy intended only for people in need may indirectly benefit donors in rich income groups with little exposure to shocks. In a very strict model of full consumption insurance, idiosyncratic household income changes should be absorbed by all other members in the same insurance network. As a result, after controlling for aggregate shocks, idiosyncratic income shocks should not affect consumption when risk sharing is efficient. The theoretical implications for the existence of complete risk-sharing arrangements within an insurance network are widely tested in the literature (Townsend, 1994; Ligon, 2008). The very strict full-insurance hypothesis does seem to be rejected statistically in most data sets, especially for the poorest farmers (Townsend, 1994). Yet, the empirical consensus suggests that, in general, the degree of missing markets is somewhat smaller than many had assumed, and many better-off households seem to face almost complete insurance and credit markets against idiosyncratic shocks (Townsend, 1994). However, natural disasters are typically rare, unexpected events through which people become burdened by sudden damage, making it even harder to design mutual insurance for natural disasters. Sawada and Shimizutani (2007) investigated to what extent victims were insured against unexpected losses caused by the Great Hanshin-Awaji (Kobe) earthquake in 1995. Their evidence overwhelmingly rejects the full consumption insurance hypothesis, suggesting the ineffectiveness of formal and informal insurance mechanisms against the risk of earthquakes.

3. Individual and Social Preferences for Insurance Mechanisms

3.1. Individual and Social Preferences

To strengthen market, state, and community insurance mechanisms, we need to develop a strong grasp of the roles of individual and social preferences. We investigate parameters associated with individual and social preferences, respectively, by eliciting deep parameters of the standard neo-classical utility function and utility functions involving social or other-regarding preferences.

The former set of individual parameters can be described by the following conventional constant relative risk aversion (CRRA) type utility function with quasi-hyperbolic discounting:

$$U(c_t, c_{t+k}) = c_t^{\alpha} + \beta\delta^k c_{t+k}^{\alpha}, \tag{1}$$

where β = degree of present bias (or quasi-hyperbolic discounting) and β = 1 if t = 0, 1- α is the coefficient of relative risk aversion, and δ is the exponential discount factor. Note that undesirable behaviours such as obesity, over-eating, debt overhang, gambling, smoking, drinking, and other procrastination behaviours have been attributed to naive hyperbolic discounting (Banerjee and Mullainathan, 2010). There are multiple ways to elicit these deep parameters, such as the dual multiple price list (DMPL) method of Andersen, *et al*. (2008) and the convex time budget method developed by Andreoni and Sprenger (2012) and Andreoni, *et al.* (2013). Note that incorporating the present bias or quasi-hyperbolic discounting in the model is an important deviation from the pure neoclassical model according to which people can make decisions wisely. In contrast to these traditional models, a growing body of work in cognitive psychology lends credence to these doubts, leading to an integrated filed in economics—behavioural economics. With this augmented framework, we believe we can investigate the seemingly irrational anomalies in people's decisions involving risks.

The "social preferences" is a formulation of a utility function which involves utility interdependency, or simply, "other-regarding preferences." Such preferences include altruism, fairness, envy, guilt, trust, reciprocity, and inequality aversion (Cooper, *et al.*, 2014). Dictator, trust, and public goods games can be adopted to quantify the degree of altruism, trust/trustworthiness, and reciprocal cooperation, respectively (Camerer and Fehr, 2004; Levitt and List, 2009; Cardenas and Carpenter, 2008).

In the dictator game, the sender, called the "dictator", is provided with an initial endowment that he/she can either keep or allocate to the receiver. Since there is no self-interested reason for the sender to transfer money, the actual positive amount of transfer is interpreted as the level of altruism (Camerer and Fehr, 2004; Levitt and List, 2009).

Following Berg, *et al*. (1995), we can conduct a standard trust game to measure trust and trustworthiness. In a trust game, all participants are at the outset endowed with an initial stake and each participant is asked as a sender to decide the amount they would send to a receiver. The committed amount of money is tripled, the transfer decision is then sent to its corresponding receiver and each receiver is asked to decide a return amount. In a standard trust game, the set of zero transfers by a receiver and a sender satisfies a sub-game perfect Nash equilibrium. Hence, deviation from zero transfers of a sender and of a receiver can be interpreted as trust and trustworthiness, respectively (Levitt and List, 2009).

In a public goods game, a decision is made within each anonymous group (Camerer and Fehr, 2004; Levitt and List, 2009; Cardenas and Carpenter, 2008). At the beginning of a game, each player is given an endowment and is asked how much to contribute in the group project, keeping the rest for him/herself. The group's total contribution is doubled and redistributed equally to all members. Since the dominant strategy of an egoistic individual is to contribute nothing to the group project, a set of zero contributions by all comprises Nash equilibrium. According to the usual interpretation of the standard experimental games used to measure social preferences, contributions in public goods games reflect reciprocal expected cooperation (Camerer and Fehr, 2004; Levitt and List, 2009; Cardenas and Carpenter, 2008).

3.2. Whether and How a Disaster Affects Preferences

Two issues need careful investigation in our context: first, whether and how a disaster affects preferences; and second, how preferences determine the vulnerability and resilience against damage caused by a disaster.

On the one hand, to identify effective policies to facilitate livelihood recovery of the victims of a disaster, it is imperative to clarify how individual and social preferences are affected by the disaster. By doing so, we can examine, for example, whether the disaster affects the poor disproportionately. In economics, individual preference parameters have long been treated as "deep parameters," i.e., as given and thus constant over time (e.g., Stigler and Becker, 1977). Studies on endogenous formation of individual and social preferences have only recently started to emerge, finding that they are not constant over time and that they change under some circumstances (Fehr and Hoff, 2011). As natural disasters and manmade disasters are traumatic events, they are likely to affect an individual's behaviour in the short term and possibly in the long term. Two notable examples of such studies, on the Indian Ocean tsunami in 2004, are Cameron and Shah (2012) and Cassar, Healy and Kesseler (2011). Cameron and Shah (2012) found that, in Indonesia, individuals who suffered a flood or earthquake in the past three years are more risk averse than those who did not. Cassar, *et al.* (2011) showed that after the tsunami in Thailand, individuals affected by the disaster were substantially more trusting, risk averse and trustworthy. They also found that individual-level welfare and aggregate growth-level are affected by changes in these social preferences. Callen, *et al*. (2014) investigated the relationship between violence and economic risk preferences in Afghanistan, finding a strong preference for certainty and violation of the expected utility framework. Most importantly, Voors, *et al*. (2012) used a series of field experiments in rural Burundi to find that individuals exposed to violence display more altruistic behaviour towards their neighbours and are more risk seeking. The results indicate that large shocks can have long-term consequences for insurance mechanisms.

The mechanisms of changing individual preferences after being exposed to a disaster, or simply endogenous preferences, can be explained in several ways. First, in the neoclassical model of the short-term adaptation of preferences developed by Becker and Mulligan (1997) individuals can decide to pay to increase their discount factor above the endowed level, allowing them to choose their effort level to change their preferences. Second, evolutionary theory can also explain non-stable preferences in which preferences are determined by matching between the individual and the environment (Robson, 2001; Robson, 2007; and Netzer, 2009). Third, Loewenstein and Lerner (2003) incorporate emotions in decision-making to explain how people discount delayed costs and benefits. Finally, Weitzman (2009) formulates a Bayesian learning model of structural uncertainty of low probability catastrophes, leading to a critical change of deep preference parameters.

3.3. How Preferences Determine the Vulnerability and Resilience

Responses to a disaster will differ according to individuals and social preferences, implying that preferences are critical determinants of vulnerability, resilience, and effectiveness of market and non-market mechanisms in coping with, reconstruction of and the rehabilitation process of a disaster. To illustrate this, we follow Morduch (1995) to capture the negative welfare costs of disaster risks by calculating how much money households would be willing to pay to completely eliminate income variability. Mathematically, this amount of money is represented by *m,* which satisfies the following relationship:[3] $u(\bar{y}-m)=E[u(\tilde{y})]$, where $u(\cdot)$ is a well-behaved utility function, $\tilde{y}$ is a stochastic income and $\bar{y}$ is its mean value. Taking a first-order Taylor expansion of the left-hand side around m=0 and a second-order Taylor expansion of the right-hand-side around the mean income gives:[4]

$$(2)\qquad \frac{m}{\bar{y}}=\frac{1}{2}\underbrace{\left(-\frac{u''(\bar{y})\bar{y}}{u'(\bar{y})}\right)}_{\text{Coefficient of RRA}}\times\underbrace{\left(\frac{\sqrt{Var(\tilde{y})}}{\bar{y}}\right)^2}_{\text{Coefficient of Variation}},$$

Equation (2) indicates that, approximately, the fraction of average income a household would be willing to give up can be calculated as half of the coefficient of relative risk aversion multiplied by the square of the coefficient of variation of income. While natural and manmade disasters generate large income volatilities, the welfare impacts are also dependent on the relative risk aversion parameter, one of the important individual preference parameters. Hence, the individual response of a disaster will be driven by a "deep" parameter.

While recent work has begun to investigate the welfare impacts of natural disasters as well as manmade disasters such as economic crises through price changes (Friedman and Levinsohn, 2002), as far as we know only few studies have examined the impacts of a disaster on victims' behavioural change.

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[3] The variable *m* represents a standard risk premium.

[4] This is the so-called Arrow=Pratt risk premium.

4. Project Summary

In this project, our first aim is to produce the academic foundations of the nexus between a disaster and individual/social preferences so that we can fill in the remaining large gap in the literature on behavioural impacts of disasters by investigating two issues: first, whether and how a disaster affects preferences; and second, how preferences determine the vulnerability and resilience against damage caused by a disaster. We believe that such a study is also indispensable in terms of designing and implementing appropriate post-disaster policies. To achieve this aim, we employ both existing data and new experiments from selected fields to quantify heterogeneous behavioural impacts of the disaster.

In order to approach the first issue, whether and how a disaster affects preferences, it is indispensable to grasp people's individual and social preferences correctly by carrying out carefully designed experiments. Canonical methods as well as a new experiment such as the "Convex Time Budget (CTB)" experiment, designed by Andreoni and Sprenger (2012), were conducted in selected sites to elicit and compare social preferences in different Asian countries and areas.

To carry out an assessment of the second issue, how preferences determine vulnerability and resilience, we employ standard and non-standard outcome measures in economics. Our outcome evaluation criteria include: standard individual decisions, particularly consumption and saving decisions based on the standard Euler equation, firm decisions and performance, psychosocial outcomes, and human capital outcomes. Basically, in each component, data on welfare measures such as consumption, ex post risk coping strategy against a disaster, and other dimensions such as social networks were collected and analysed by using multi-purpose household survey instruments together with the carefully designed experiments. Also, we employ relatively new measures in economics such as management practices and psychosocial measures as outcome measures. The former aspects have been studied extensively by Bloom, *et al*. (2014). The latter measure is to capture post-traumatic stress disorder (PTSD), which has been studied extensively in public health and social epidemiology literature.

To strengthen market, state, and community insurance mechanisms, we need to have a strong grasp of the roles of individual and social preferences. By employing these combined data sets, we identify effective policies to facilitate livelihood recovery of the victims of a disaster, considering closely people's behavioural responses against unexpected events caused by a variety of natural and man-made disasters. Through this project, we provide important policy implications for better insurance mechanisms at community, national, and regional level, generating inputs for high-level forums of the Association of Southeast Asian Nations (ASEAN) and East Asia.

4.1. Summary of Chapters

This report begins with the most frequently occurring type of disaster in East and Southeast Asia—hydro-meteorological disasters. More specifically, floods in the Philippines, Cambodia, Thailand, and Viet Nam are investigated. The Viet Nam chapter also investigates other disasters such as avian influenza. The second set of papers looks at the impact of geological disasters in Japan and China: the Great East Japan Earthquake and the Great Sichuan Earthquake in China. The third paper in this set investigates the consequences of a technological disaster—the Fukushima Dai-ichi nuclear power plant accident, induced by the Great East Japan earthquake. The final paper examines a variety of business risks in Lao PDR. Table 1.2 gives an overview of the chapters included in this report.

Table 1.2: A List of Chapters

Country	Philippines	Cambodia	Thailand	Viet Nam
Disaster type	*Flood*	*Flood*	*Flood*	*Flood, AI, Drought and other disasters*
Targeted preferences	Risk attitude Time discount Social preference	Risk attitude Time discount Social preference	Risk attitude Time discount Social preference	Risk attitude Time discount
Other outcomes	Risk coping	Risk management and coping	Risk management and coping	Insurance demand

Country	Iwanuma (and Sendai) Japan	China	Fukushima, Japan	Lao PDR
Disaster type	*Tsunami*	*Earthquake*	*Technology*	*Export market Technology*
Targeted preferences	Risk attitude Social preference	Risk Social preference	Psychosocial	Risk attitude
Other outcomes	Psychosocial	Test score (cognitive) Psychosocial & pro-social	Programme evaluation Psychosocial	Investment & production Safety

Note “AI = Asian influenza.

4.2. Hydro-meteorological and Biological Disasters

The second chapter by Yasuyuki Sawada and Yusuke Kuroishi, “How does a Natural Disaster Affect People's Preference? The Case of a Large Scale Flood in the Philippines using the Convex Time Budget Experiments” is an attempt to contribute to the literature on individual preferences and disasters by investigating the impact of a natural disaster on present bias, time discount, and risk aversion parameters, which are elicited by a new experimental technique called the Convex Time Budget (CTB) experiments developed by Andreoni and Sprenger (2012). They employed a unique experimental data set collected from a village in the Philippines, which was hit by a strong flood in 2012. Their focus is on the overall impact of the flood on preferences and decisions. They found the following three empirical results. First, the CTB experiments offer reasonable levels of time discounting, curvature and quasi-hyperbolic discounting in the whole sample. Second, this quasi-hyperbolic discounting in a Filipino village is contrasted with the dynamically consistent time preferences in the United States found by Andreoni and Sprenger. Finally, they found that being hit by the flood makes individuals significantly more present-biased than those who are unaffected by the flood.

In the third chapter, "The Consequences of Natural Disasters on Preferences, Risk Assessments, and Behaviours: Evidence from Thai Farmers After the 2011 Mega Flood," Krislert Samphantharak and Sommarat Chantarat assess the impact of the 2011 mega flood in Thailand on subjective expectations, preferences, and behaviours of the Thai farming households affected by the disaster. First, they found that the flood seemed to make the households adjust upward their subjective expectations on future flood events and on possible damage caused by future floods. The flood also affected the expectation of the households of government's assistance. However, they found no evidence of moral hazard arising from the government implicit insurance through disaster assistance. Second, the 2011 mega flood was positively associated with higher risk aversion and more risk averse households were more likely to adopt such strategies. Finally, they found that households directly hit by the flood seemed to be less altruistic. These findings shed light on the credibility of government assistance in the presence of widespread natural disasters and the future role of the government and insurance markets in natural disaster risk management.

The fourth chapter, "The Effects of Natural Disasters on Household's Preferences and Behaviour: Evidence from Cambodian Rice Farmers After the 2011 Mega Flood," by Sommarat Chantarat, Kimlong Chheng, Kim Minea, Sothea Oum, Krislert Samphantharak and Vathana Sann studies the impacts of the 2011 mega flood on preferences, subjective expectations, and behavioural choices among the Cambodian rice-farming households affected by the disaster. They found the flood victims to have larger risk aversion and altruism, and lower impatience with and trust of friends and local governments. The disaster further induced flooded households to adjust upward their expectations of future floods and use of natural resources as safety net. Mediating (partially if not all) through these changes in preferences and expectations, the 2011 flood also affected households' behavioural choices, some of which could determine long-term economic development and resilience to future floods. They found the flooded households to have lower productive investment and to substitute social insurance with an increasing reliance on private insurance, increasing demand for market-based instruments. They also increased the use of natural resources as insurance. Asian These findings shed light on the design of incentive-compatible safety nets and development interventions.

Chapter 5, "Time Preference, Risk and Credit Constraints: Evidence from Viet Nam," by Hiroyuki Nakata and Yasuyuki Sawada empirically examines the effects of the environment on time preferences of economic agents by using a unique household data set collected in Viet Nam. The environment includes credit constraints and recent loss experience, in terms of frequency, the nature of losses and the causes of losses (types of disasters). Subjective interest rates exhibit inverted yield curves, consistent with the existing results from laboratory experiments and field surveys, but are contrary to what usually can be observed in the financial markets. The empirical analyses indicate that recent past loss experience has a significant impact on subjective overnight interest rates. Also, they estimate Euler equations of a time-additive discounted expected utility model that admits quasi-hyperbolic discounting with a power utility. The results suggest that experience of losses from Asian influenza (AI)an and/or floods has an impact on time preference parameters, although the impacts are not robust when the impacts of AI or flood losses through credit constraints are taken into account, suggesting possible inadequacies in the specification of the model.

4.3. Geological and Technological Disasters

Chapter 6 by Yasuyuki Sawada and Yusuke Kuroishi titled, "How To Strengthen Social Capital in Disaster Affected Communities? The Case of the Great East Japan Earthquake," investigates the nexus between damage caused by the disaster and preference parameters, as well as the impact of individual preference on social capital. They employ unique field experiment data collected exclusively for this study from the residents of Iwanuma city, located near Senday city in Miyagi Prefecture, who were affected by the March 11th earthquake and tsunami. They conducted carefully designed artefactual experiments using the methodology of the Convex Time Budget (CTB) experiments of Andreoni and Sprenger (2012) to elicit present bias, time discount, and risk preference parameters. They also conducted canonical dictator and public goods games to capture the pro-social behaviour of the subjects of the experiments. Several important findings emerged: First, they found an absence of quasi-hyperbolic discounting in the whole sample. Second, they found that the damage from the disaster seems to have made individuals more present-biased. Third, in dictator games, the amounts of money sent to victims of Great East Japan Earthquake are larger than those sent to anonymous persons in Japan. Also, they found that the present bias parameter and time discount factor are both negatively related to the amount of donations, implying that seemingly altruistic behaviour might be driven by myopic preference. Finally, they found that present bias is closely related to bonding social capital.

In Chapter 7 titled “Natural Disasters and Human Capital Accumulation: The Case of the Great Sichuan Earthquake in China," Albert Park, Yasuyuki Sawada, Heng Wang and Sangui Wang employ original micro data collected from students and schools affected by the Great Sichuan Earthquake in 2008 to uncover the impacts of the earthquake on the broad human capital of students, i.e., their cognitive and non-cognitive outcomes. Two main findings emerge from their empirical analysis. First, the household-level shocks from the earthquake worsen children’s psychosocial outcomes as well as family environment uniformly. Second, classroom relocations as a result of the earthquake mitigate depression, enhance self-esteem, improve family environment, and improve Chinese test scores. These effects may reflect positive peer effects through the earthquake-affected students’ unexpected exposure to students and facilities in better schools. Since non-cognitive skills may be more malleable than cognitive skills at later ages, the government can play an important role in facilitating human capital accumulation in a broader sense by effectively amending the non-cognitive skills of children affected by a natural disaster directly or indirectly.

Due to grave concerns about radiation exposure after the nuclear power plant accident caused by the Great East Japan earthquake, many parents in

Fukushima prohibited their children from playing outdoors. The Japanese Red Cross organized short-term and large-scale indoor park programmes for preschool children across Fukushima to in an effort to reduce high stress levels among children. Chapter 8, “Do Short-term Indoor Park Programmes Improve Preschool Children’s Psychological Health in Fukushima?” by Chishio Furukawa and Yasuyuki Sawada aimed to quantify the impact of the short-term indoor park programmes on the children’s psychological health. They used a Strengths and Difficulties Questionnaire to assess the children’s psychological health condition. While no causal statement may be made regarding the programme's effectiveness due to lack of randomization, participation in the programme is not negatively correlated with stress levels on average; unexpectedly, there were a few signs of positive correlation with overall stress levels and negative correlation with pro-social behaviour. This correlation was largely found among the children whose parents always prohibit them from playing outdoors and regularly use the indoor playground facilities. This may be due to an actual impact, reporting bias (those who want the programme to continue may overstate the stress level as evidence of the need for the programme), or reverse causality. They also find that stress is correlated with experience of evacuation and parents' prohibition of outdoor play, but this does not apply to those who participated in the regular indoor programmes.

4.4. Business Risks in an Emerging Economy

While there have been numerous micro-econometric studies on risk and poverty in rural developing economies, there have only been a few studies on business risks arising from volatile input and output prices and weak enforcement of contracts. In Chapter 9, “Risk Preference of Managers and Firm Investments in Lao PDR,” Mari Tanaka and Yasuyuki Sawada aim to bridge this gap in the literature through their analysis of a unique survey and experiment data from textile and garment firms in Lao PDR, collected exclusively for their study. To investigate the role of risk preference of firm managers on a variety of firm investment decisions, they elicited measures of managers’ risk preferences through experiments. They found that firms with risk adverse managers are more likely to self-finance investments than to borrow from banks or informal sources, leading to lower overall asset levels. A risk averse firm manger is more likely to face binding “self-inflicted” borrowing constraints on additional investments. However, their results also indicated that risk averse managers invest more in their factories' safety measures against fires and injuries. In addition, they examine the association between risk preference of managers and adoption of management practices. While the results are not statistically significant, they find that risk tolerant managers are more likely to have adopted better practices and have achieved employment stability.

5. Policy Implications

There are several policy implications from the findings of our research project.

First, the poor might be significantly risk averse and present-biased as in the case of farmers in the Philippines, Thailand, Viet Nam, and Cambodia. Natural disasters make the poor more present-biased and risk averse than those who are unaffected by disasters. Accordingly, disasters seem to weaken the effectiveness of the pre-existing informal network of social safety nets Such impacts of disasters may stimulate people's too much dependence on financial and non-financial assistance from the government, donor agencies, and NGOs, undermining sound post-disaster reconstruction or "building back better." Reinforced present-bias may induce substantial procrastination behaviors such as over-eating, over-spending, drinking, smoking, gambling, and over-indebtedness. Risk aversion would also facilitate procrastination behaviors. Since careless cash and in-kind transfers to the victims will worsen procrastination behaviors, the government and donor agencies should carefully design incentive-compatible safety net and development interventions to establish "commitments" against procrastination behaviors. Examples may include carefully-designed in-kind or voucher transfers rather than pure cash transfers, disaster loan programs, and commitment micro-saving programs.

Second, the importance of individual preferences can be also found in business investments. As found in the case of Lao PDR, firms with risk adverse managers are more likely to self-finance investments rather than to employ borrowing from a bank or other informal sources, leading to lower overall asset level. A risk averse firm manger is more likely to face binding "self-inflicted" borrowing constraints on additional investments. Risk tolerant managers, are more likely to have adopted better practices and to achieve employment stability. To facilitate "resilient" firm investments, it will be indispensable to make managers take risks (promoting entrepreneurship) by providing effective insurance mechanisms against business related risks. Concrete examples may include business information sharing network, credit guarantee system, and public facilitation of trade credit.

Third, natural disasters generate not only economic damages but also serious psychosocial and family problems as shown in the case of the Great Sichuan Earthquake in China and preschool children's psychological health in Fukushima. Such negative impacts seem to be large among children and teenagers who are in an important phase of accumulating their human capital. Since non-cognitive skills may be more malleable than cognitive skills at later ages, the government must play an important role in facilitating human capital accumulation of the young who are affected natural disasters in a broader sense effectively by amending not only cognitive skills at school but also the non-cognitive skills of the victimized children and teenagers directly or indirectly. In addition to rehabilitation of infrastructure and reconstruction of family and community economies, special cares and resources should be provided at schools and out of schools to amend psychosocial damages caused on the students. Carefully-designed "rehabilitation camps" for the affected children may also be effective to weather the problems.

In sum, it would be imperative to strengthen market, state, and community insurance mechanisms by promoting risk control and financing instruments such as "hard" insurance schemes within each country and across countries in the region. Yet, we also need to place special care on subtle psychosocial and behavioral problems of the victimized children, teenagers, business managers, and other ordinal people.

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CHAPTER 2

How Does a Natural Disaster Affect People's Preference? The Case of a Large Scale Flood in the Philippines Using the Convex Time Budget Experiments

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This paper is an attempt to contribute to the literature on individual preferences and disasters by investigating the impact of a natural disaster on present bias, time discount, and risk aversion parameters, which are elicited by using a new experimental technique called the Convex Time Budget (CTB) experiments, developed by Andreoni and Sprenger (2012), as well as a more common method called the Double Multiple Price List (DMPL) experiments of Andersen, Harrison, Lau and Rutström (2009). We also conducted canonical dictator games to elicit degree of altruism, one of the most widely analysed social preferences. Based on these methods, we employed a unique experimental data set collected from a village in the Philippines, which was hit by a strong flood in 2012. Our focus is on the overall impact of the flood on preferences and decisions. We found the following three empirical results: First, the CTB experiments offer reasonable levels of time discounting, curvature and quasi-hyperbolic discounting in the whole sample. Second, this quasi-hyperbolic discounting in a Filipino village is contrasted with the dynamically consistent time preferences in the United States found by Andreoni and Sprenger. Finally, we found that being hit by the flood made individuals significantly more present-biased than those who were unaffected by the flood.

Keywords: Convex Time Budget experiment, Natural Disaster, Risk and Time Preference

***JEL Classification*:** C93,D81,O12

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1. Introduction

Recently, a number of devastating natural disasters have hit both developed and developing countries. Hundreds of thousands of lives were lost in the 2013 Typhoon Haiyan (Yolanda) in the Philippines, the 3/11 compounded disaster in Tohoku, Japan in 2011, and the 2008 Sichuan earthquake in China. In 2011, the floods in Thailand involved relatively few human casualties, but caused USD 45.7 billion in damage, mainly to the manufacturing sector, as seven major industrial estates were inundated by floods. Disasters can have serious negative effects not only in terms of lives lost, but also on the livelihoods of survivors in the aftermath of the disaster.

In preparation for and response to the wide variety of shocks caused by natural disasters, people can adopt market insurance mechanisms, make use of government ex ante and ex post support, and use informal mutual insurance mechanisms in their community. To improve complementarities among these market, state, and community insurance mechanisms, we need to understand the roles of individual decisions and behaviours. In particular, we need to examine how individual and social preferences—the foundations of decision-making—are affected by disasters.

In economics, individual preference parameters have long been treated as “deep parameters,” i.e., as given and thus constant over time (e.g., Stigler and Becker, 1977). Moreover, the pro-social behaviours or social preferences of individuals, usually modeled as a deviation from Nash equilibrium, have been regarded as "irrational" decisions. Studies on endogenous formation of individual and social preferences have only recently started to emerge, finding that they are not constant over time and that they change under some circumstances (Fehr and Hoff, 2011). As natural disasters and manmade disasters are traumatic events, they are likely to affect an individual’s behaviour in the short term and possibly in the long term. Notable examples of such studies, on the Indian Ocean tsunami in 2004, are Cameron and Shah (2011) and Cassar, *et al.* (2011), as well as Callen, *et al*. (2014) on Afganistan, and Voors, *et al*. (2012) on Burundi. Cameron and Shah (2012) found that, in Indonesia, individuals who suffered a flood or earthquake in the past three years are more risk averse than those who did not. Cassar, *et al.* (2011)

showed that after the tsunami in Thailand, individuals who were affected by the disaster were substantially more trusting, risk averse and trustworthy. They found that individual-level welfare and aggregate growth-level are affected by changes in these social preferences. Callen, *et al*. (2014) investigated the relationship between violence and economic risk preferences in Afghanistan, finding a strong preference for certainty and violation of the expected utility framework. Most importantly, Voors, *et al*. (2012) used a series of field experiments in rural Burundi to find that individuals exposed to violence display more altruistic behaviour towards their neighbors and are more risk seeking. The results indicate that large shocks can have long-term consequences for non-market insurance mechanisms. While there have been developed empirical studies on household behaviour toward risks in developing countries, changes in individual parameters and behaviours by disasters still have remained to be largely identified.

In this paper we investigate the impact of a natural disaster on present bias, time discount, and risk aversion parameters, which are elicited by a new experimental technique called the Convex Time Budget (CTB) experiments, developed by Andreoni and Sprenger (2012) as well as the canonical experiments called the Double Multiple Price List (DMPL) experiments of Andersen, *et al*. (2008), in an integrated manner. We employ a unique experimental data set collected from a village in the Philippines, which was hit by a strong flood in 2012. Our focus is on the overall impact of the flood on preferences and decisions. Indeed, the Philippines suffers from tropical depression and typhoons nearly every year the country experiences about 20 tropical storms on average every year, usually occurring during the monsoon season from June to December.

2. Data

We studied residents in East Laguna village, which is located in the Pila municipality of Laguna province, approximately 80 kilometers south of Metro Manila, facing the east coast of Laguna de Bay. Its proximity to the International Rice Research Institute (IRRI), which is located in Los Baños and 20 kilometers away from the village, has enabled researchers to conduct surveys in cooperation with IRRI. The earliest documented survey carried out in the village dates back to 1966, when a Japanese geographer, Hiromitsu Umehara (1967), conducted and reported the results of a total enumeration survey. After Umehara’s first survey, 18 rounds of household surveys were conducted from 1974 to 2007 in collaboration with IRRI (Sawada, *et al*., 2012). Surveys in the 1970s, 1980s, and 1990s were organised predominantly by Professor Yujiro Hayami and Professor Masao Kikuchi, who made numerous international academic contributions (Hayami and Kikuchi, 2000). They found that due to the increase in rice production and the fall in the price of rice, both of which were to some extent induced by the Green Revolution and land reform implementation, the income of agricultural households and food consumption of poor households increased significantly. They also found that a boost in non-agricultural income was a result of investment in education financed by the increased income from agricultural activities. In the 2000s, five further rounds of surveys were conducted by other researchers (Fuwa, *et al*., 2006; Kajisa, 2007; Sawada, *et al*., 2012). Due to these numerous surveys, a lot of benchmark information on the village has been collected, compiled, and carefully analysed.

In August 2012, the village was hit by serious flooding due to the southwest monsoon rains, also known as "habagat" in Tagalog. It had started with an eight-day period of torrential rains and thunderstorms in the Philippines from August 1st to August 8th. Its effects centered on Metro Manila, the surrounding provinces of the CALABARZON Region (Quezon, Cavite, Laguna and Rizal provinces) and the provinces of Region 3 (Bulacan, Pampanga and Bataan Provinces). Not a typhoon in its own right, the storm was a strong movement of the southwest monsoon "habagat" caused by the pull of Typhoon Saola (Gener) from August 1-3, strengthened by Typhoon Haikui. It caused typhoon-like damage such as river overflow and landslides to the region. In Laguna province, where East Laguna Village is located, "habagat" spawned flooding that submerged low-lying villages in 19 towns and cities including the village, destroying PhP 410.3 million worth of agriculture products. The damaged crops were planted in about 11,000 hectares of inundated farmlands of rice, corn and crops, and affected some 6,000 farmers. More than a half of the village area was submerged by floodwater, causing great damage to rice paddies.

We employ survey and experimental data collected exclusively for this study. The subjects were selected from the farmers in East Laguna village and surrounding villages. A total of 161 farmers participated in our field experiments on March 20th (34 participants), March 21st (32 participants), March 22nd (38 participants), March 23rd (40 participants), and March 24th (17 participants) in 2014.

3. Estimation Models

We carefully design and conduct two types of experiments to elicit present bias, time discount, and risk aversion parameters: First, we adopt a new experimental technique called the Convex Time Budget (CTB) experiments developed by Andreoni and Sprenger (2012); and second, we employ the canonical experiments called the Double Multiple Price List (DMPL) experiments of Andersen, *et al*. (2008). The data collected by both the CTB and DMPL experiments in the village are used to separately identify the three key parameters of the utility function: risk aversion parameter, 1-α; time discounting parameter, δ; and present bias parameter, β.

For the CTB and the DMPL, we assume a quasi-hyperbolic discounting structure for discounting and the preferences described by:

$$U(x) = x_t^{\alpha} + \beta \sum_{k=1}^{\infty} \delta^k x_{t+k}^{\alpha}, \tag{1}$$

where the parameter δ captures standard long-run exponential discounting, and the parameter β captures a specific preference towards payments in the present, $t = 0$. While present bias is associated with $\beta < 1$, $\beta = 1$ corresponds to the case of standard exponential discounting. Also, $1-\alpha$ represents the coefficient of relative risk aversion.

3.1.The Convex Time Budget (CTB) Experiment

In the CTB experiment of Andreoni, *et al.* (2013), subjects are given the choice of (X, 0), (0, Y) or anywhere along the intertemporal budget constraint connecting these points, such that $Px_t + x_{t+k} = Y$, where $P = \frac{Y}{X}$ is the gross interest rate. In this setting, we can maintain a standard intertemporal Euler equation:

$$MRS = \frac{x_t^{\alpha-1}}{\beta^{1\{t=t_0\}}\delta^k x_{t+k}^{\alpha-1}} = P$$

where t_0 is an indicator for whether $t = 0$. This can be rearranged to be linear in t, k, and P,

$$ln(\frac{x_t}{x_{t+k}}) = \frac{ln(\beta)}{\alpha-1}t_0 + \frac{ln(\delta)}{\alpha-1}k + \frac{1}{\alpha-1}ln(P) \qquad (3)$$

Assuming an additive error structure, this is estimable at either the whole group or individual level.

However, the allocation ratio $ln(\frac{x_t}{x_{t+k}})$ is not well defined at corner solutions. To address this problem, we can use the demand function to generate a non-linear regression equation based on

$$x_t = \frac{400(\beta^{t_0}\delta^k P)^{\frac{1}{\alpha-1}}}{1+P(\beta^{t_0}\delta^k P)^{\frac{1}{\alpha-1}}} \qquad (4)$$

which avoids the problem of the logarithmic transformation in (2).

3.2.The Double Multiple Price List (DMPL) Experiment

The DMPL consists of two stages (Andersen, *et al*., 2008). The first stage is designed to identify discounting. The second stage is designed to unconfound the first stage by providing information on utility function curvature through risky choice.

3.2.1. The Multiple Price List (MPL) Experiment

In the Multiple Price List (MPL) experiment, individuals make a series of binary choices between smaller sooner payments *X* and larger later payments

Y. The point in each price list where an individual switches from preferring the smaller sooner payment to the larger later payment carries interval information on discounting. In MPL, we assume α = 1. Then, from Andersen, *et al*. (2008), the probability of choosing the smaller sooner payments *X* can be formalised as:

$$Pr(Choice = X) = \frac{(\beta^{t_0}\delta^k X)^{\frac{1}{v}}}{(\beta^{t_0}\delta^k X)^{\frac{1}{v}} + (\beta^{t_0}\delta^k Y)^{\frac{1}{v}}} \tag{5}$$

where ν represents stochastic decision error. On the other hand, the probability of choosing the larger later payment is

$$Pr(Choice = Y) = \frac{(\beta^{t_0}\delta^k Y)^{\frac{1}{v}}}{(\beta^{t_0}\delta^k X)^{\frac{1}{v}} + (\beta^{t_0}\delta^k Y)^{\frac{1}{v}}} \tag{6}$$

In order to estimate parameters, β, δ, and ν, we can maximise the following conditional log-likelihood function:

$$lnL(\beta, \delta, v; X, Y) = \sum_i \mathbf{1}\{Choice = X\} ln(Pr(Choice = X) + \mathbf{1}\{Choice = Y\} ln(Pr(Choice = Y) \tag{7}$$

3.2.2 The Holt and Laury (2002) Experiment

The Holt and Laury (2002) experiment is one of the most popular experiments to elicit an individual's attitude toward risks. In the Holt and Laury (2002) experiment, subjects face a series of decisions between a safe and risky binary (gamble) choice. The probability of the high outcome in each gamble increases as one proceeds through the task,such that where a subject switches from the safe to the risky gamble carries information on risk attitudes. In Holt and Laury, there are two options, A and B. For each outcome of each option A and B, the probability $p(M_{ij})$ is assigned by the experimenter. Then, the expected utility for lottery i (i

= A or B) is

$$EU_i = \sum_{j=1,2} (p(M_{ij}) \times M_{ij}^{\alpha}) \tag{8}$$

The probability of choosing the safe binary gamble, the option A, is

$$Pr(Choice = A) = \frac{EU_A^{\frac{1}{\mu}}}{EU_A^{\frac{1}{\mu}} + EU_B^{\frac{1}{\mu}}} \tag{9}$$

where μ represents stochastic decision error. On the other hand, the probability of choosing the risky binary gamble, option B, is

$$Pr(Choice = B) = \frac{EU_B^{\frac{1}{\mu}}}{EU_A^{\frac{1}{\mu}} + EU_B^{\frac{1}{\mu}}} \tag{10}$$

Then the conditional log-likelihood function to estimate parameters, α and μ, is

$$lnL(\alpha, \mu; A, B) = \sum_i \mathbf{1}\{Choice = A\} ln(Pr(Choice = A) + \mathbf{1}\{Choice = B\} ln(Pr(Choice = B) \tag{11}$$

3.2.3. The Double Multiple Price List (DMPL) Experiment

Combining the two multiple price list experiments shown above, in the double multiple price list (DMPL) experiments, the joint likelihood of the curvature and discount rate becomes:

$$lnL(\beta, \delta, \alpha, \mu, \nu; X, Y, A, B) = lnL^{RA} + lnL^{DR} \tag{12}$$

which is maximised using standard numerical methods.

4. Results

4.1. The Convex Time Budget (CTB) Experiment

Table 2.1 shows the estimation results of the curvature parameter, α, which is associated with risk aversion parameter, 1- α; time discounting parameter, δ; and present bias parameter, β. The first two columns report the estimated parameter based on equation (4) using non-linear least squares (NLS) and the last column shows results based on equation (3) using ordinary least squares (OLS). In all specifications, the estimated present bias parameter falls significantly below one, indicating substantial quasi-hyperbolic discounting in the whole sample. Time discount and risk aversion parameters are within a reasonable range.

Table 2.1: The Results of Aggregate CTB

	(1) NLS	(2) NLS	(3) OLS
β	0.827***	0.827***	0.788***
	(0.0166)	(0.0204)	(0.0266)
δ	0.993***	0.993***	0.992***
	(0.000272)	(0.000639)	(0.000868)
α	0.738***	0.738***	0.854***
	(0.0130)	(0.0200)	(0.0134)
Clustered SE's	No	Yes	Yes
N	2880	2880	2880

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In order to examine the impact of disasters, we re-estimate the model allowing for a heterogenous risk aversion associated parameter, α; time discounting parameter, δ; and present bias parameter, β, depending on the seven damage types: (1) overall damage; (2) house damage; (3) farm damage; (4) asset damage; (5) income loss; (6) increasing in debt; and (7) sickness or injury. The results are shown in Table 2.2 where subscript "zero" and "one" indicate "without damage" and "with damage," respectively. In this table, we can verify that the disaster affected the present bias parameter negatively though not necessarily significantly. Only house damage caused negative and significant impact on the present bias parameter.

Table 2.2.: The Effect of Habagat on Deep Parameters in CTB

	(1) None	(2) House	(3) Farm	(4) Assets	(5) Income	(6) Debt	(7) Sick or Injured	(8) Day = 3 or 4
β_0	0.878***	0.814***	0.773***	0.792***	0.837***	0.802***	0.796***	0.824***
	(0.0783)	(0.0286)	(0.0647)	(0.0283)	(0.0520)	(0.0308)	(0.0284)	(0.0366)
β_1	0.784***	0.698***	0.791***	0.745***	0.775***	0.771***	0.721***	0.749***
	(0.0275)	(0.0633)	(0.0290)	(0.0703)	(0.0307)	(0.0455)	(0.0756)	(0.0377)
δ_0	0.993***	0.992***	0.992***	0.992***	0.991***	0.993***	0.992***	0.991***
	(0.00269)	(0.000857)	(0.00182)	(0.000907)	(0.00246)	(0.000963)	(0.000874)	(0.00117)
δ_1	0.992***	0.989***	0.991***	0.990***	0.992***	0.990***	0.990***	0.992***
	(0.000901)	(0.00264)	(0.000988)	(0.00286)	(0.000893)	(0.00153)	(0.00371)	(0.00130)
α_0	0.883***	0.862***	0.849***	0.854***	0.818***	0.865***	0.854***	0.852***
	(0.0345)	(0.0143)	(0.0279)	(0.0141)	(0.0371)	(0.0166)	(0.0141)	(0.0196)
α_0	0.852***	0.825***	0.855***	0.854***	0.863***	0.839***	0.850***	0.855***
	(0.0140)	(0.0346)	(0.0152)	(0.0444)	(0.0139)	(0.0218)	(0.0433)	(0.0181)
$\beta_0 = \beta_1$	0.25	0.09	0.79	0.54	0.30	0.58	0.35	0.15
$\delta_0 = \delta_1$	0.65	0.20	0.74	0.46	0.60	0.13	0.56	0.75
$\alpha_0 = \alpha_1$	0.41	0.32	0.84	0.98	0.25	0.34	0.93	0.91
Clustered SE's	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2880	2880	2880	2880	2880	2880	2880	2880

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.1 and Table 2.3 show the distribution of the incidence of damage caused by the flood. By using this damage information, we can construct a damage variable, which takes one if the incidence of damage is three or more; and takes zero if the incidence of damage is either one or two. We then allow the three deep parameters to differ depending on the damage status. The results are presented in Table 2.4 where subscript "zero" indicates "without damage" and "one" indicates "with damage." These estimation results indicate that individuals hit by the flood became significantly more present-biased than those unaffected by the flood.

Figure 2.1: Damage Levels by Habagat

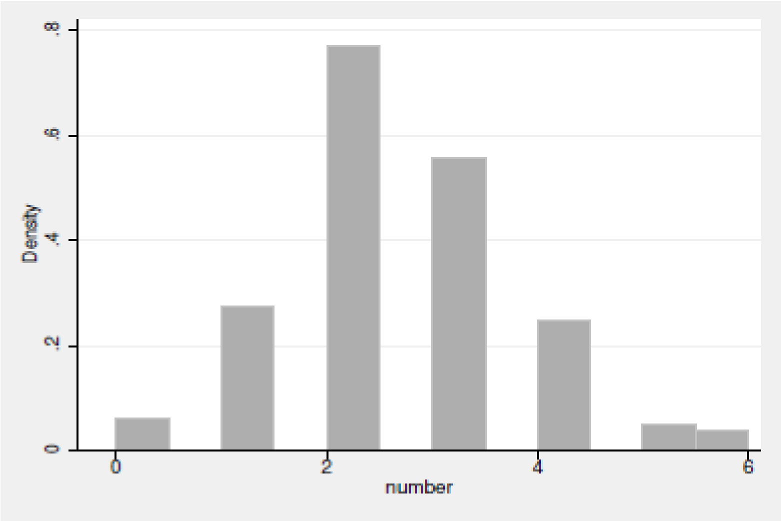


Table 2.3: The Number of the Damages

Item	Number	Per cent
0	5	3
1	22	14
2	62	39
3	45	28
4	20	12
5	4	2
6	3	2
Total	161	100

*Source:Data_ExperimentGame_PilaMarch*2014

Table 2.4: The Number of the Damages= 0/1 vs 4/5 or 0/1 vs 3/4/5/6

	(1) Severeness	(2) Severeness1
β_0	0.861***	0.811***
	(0.0495)	(0.0317)
β_1	0.640***	0.640***
	(0.0802)	(0.0796)
δ_0	0.992***	0.993***
	(0.00190)	(0.000959)
δ_1	0.989***	0.989***
	(0.00320)	(0.00318)
α_0	0.834***	0.864***
	(0.0397)	(0.0158)
α_1	0.822***	0.822***
	(0.0455)	(0.0452)
$\beta_0 = \beta_1$	0.023	0.049
$\delta_0 = \delta_1$	0.358	0.233
$\alpha_0 = \alpha_1$	0.841	0.384
N	1080	2112

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 The Double Multiple Price List (DMPL) Experiment

Table 2.5 shows estimation results of the three parameters, together with error parameters, using the double multiple price list (DMPL) experiments. Again, we can verify substantial present- bias. Yet, risk aversion parameters are unreasonably high, which may be an artifact of the experimental data treatment: For the results shown in Table 2.5, we treat the multiple switchers in the Hold and Laury experiment as single switchers by considering the first switching point only. Naturally, this may cause upward bias of the estimated risk attitude parameter, making utility function convex rather than concave. To verify this reasoning, we split our sample into the individuals without multiple switching and with switching. As we can see from Table 2.7, the risk preference parameter is substantially smaller if we use the non-switching samples only. This result supports the upward bias of the estimated risk preference parameter we had already found.

Table 2.5: The Results in Aggregate DMPL

	(1) DMPL	(2) HL	(3) MPL
β	0.516^{***}		0.608^{***}
	(0.062)		(0.057)
δ	0.970^{***}		0.974^{***}
	(0..0025)		(0.002)
α	1.254^{***}	1.255^{***}	
	(0.158)	(0.082)	
v	0.383^{***}		0.363^{***}
	(0.062)		(0.030)
μ	0.554^{***}	0.553^{***}	
	(0.060)	(0.049)	
Clustered SE's	Yes	Yes	Yes
N	17268	16692	3862

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.6: The Dummy Variable of Switching (Holt Laury)

Item	Number	Per cent
NO Switching	85	53
Switching	76	47
Total	161	100

Table 2.7: DMPL considering Switching

	(1) No Switching	(2) Switching
δ	0.965^{***}	0.975^{***}
	(0.00348)	(0.00349)
v	0.0906^{**}	0.961^{***}
	(0.0314)	(0.183)
β	0.404^{***}	0.697^{***}
	(0.0718)	(0.101)
α	0.352^{**}	2.451^{***}
	(0.123)	(0.183)
μ	0.170^{**}	0.459^{***}
	(0.0593)	(0.0340)
N	10500	6768

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To examine the impact of disasters, we re-estimate the model allowing for a heterogenous risk aversion parameter, α; time discounting parameter, δ; and present bias parameter, β depending on the seven damage types: (1) overall damage; (2) house damage; (3) farm damage; (4) asset damage; (5) income loss; (6) increasing in debt; and (7) sickness or injury. The results are shown in Table 2.8, where subscript "zero" and "one" indicate "without damage" and "with damage,"respectively. The overall results in this table show that the disaster did not affect the present bias parameter negatively. The estimation results of the Holt and Laury (2002) experiments also show that the disaster did not affect risk preference parameter (Table 2.9).

Table 2.8: The Effect of Habagat on Deep Parameters in DMPL

	(1) None	(2) House	(3) Farm	(4) Assets	(5) Income	(6) Debt	(7) Sick	(8) Day
δ_0	0.970***	0.969***	0.965***	0.970***	0.972***	0.972***	0.969***	0.971***
	(0.00682)	(0.00282)	(0.00540)	(0.00263)	(0.00448)	(0.00363)	(0.00262)	(0.00316)
δ_1	0.969***	0.972***	0.970***	0.961***	0.968***	0.967***	0.975***	0.967***
	(0.00259)	(0.00533)	(0.00282)	(0.00674)	(0.00302)	(0.00335)	(0.00774)	(0.00405)
ν_0	0.549**	0.353***	0.453***	0.372***	0.488***	0.322***	0.377***	0.444***
	(0.186)	(0.0656)	(0.123)	(0.0649)	(0.122)	(0.0926)	(0.0628)	(0.0916)
ν_1	0.374***	0.496**	0.362***	0.472*	0.344***	0.430***	0.440	0.302***
	(0.0645)	(0.170)	(0.0711)	(0.221)	(0.0716)	(0.0848)	(0.317)	(0.0840)
β_0	0.766+	0.531***	0.394***	0.518***	0.545***	0.491***	0.493***	0.535***
	(0.437)	(0.0721)	(0.105)	(0.0658)	(0.124)	(0.0880)	(0.0643)	(0.0753)
β_1	0.508***	0.473***	0.547***	0.472***	0.504***	0.546***	0.720***	0.490***
	(0.0618)	(0.117)	(0.0728)	(0.116)	(0.0710)	(0.0842)	(0.183)	(0.0999)
α_0	2.304**	1.237***	1.654***	1.229***	1.659***	1.000***	1.299***	1.506***
	(0.825)	(0.181)	(0.392)	(0.168)	(0.355)	(0.240)	(0.166)	(0.217)
α_1	1.214***	1.303***	1.157***	1.481***	1.116***	1.487***	0.861+	0.955***
	(0.160)	(0.319)	(0.171)	(0.443)	(0.172)	(0.212)	(0.471)	(0.225)
μ_0	0.569***	0.546***	0.703***	0.559***	0.743***	0.508***	0.564***	0.605***
	(0.146)	(0.0688)	(0.133)	(0.0657)	(0.127)	(0.104)	(0.0626)	(0.0750)
μ_1	0.543***	0.574***	0.510***	0.481***	0.479***	0.565***	0.422*	0.456***
	(0.0623)	(0.125)	(0.0679)	(0.146)	(0.0692)	(0.0730)	(0.213)	(0.0960)
$\beta_0 = \beta_1$	0.558	0.672	0.230	0.729	0.774	0.651	0.241	0.722
$\delta_0 = \delta_1$	0.963	0.609	0.356	0.192	0.435	0.250	0.456	0.444
$\alpha_0 = \alpha_1$	0.194	0.857	0.244	0.595	0.250	0.128	0.379	0.077
N	17268	17268	17268	17268	17268	17268	17268	17268

Clustered Standard errors in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.9: The Effect of Habagat on Deep Parameters in Holt and Laury

	(1) None	(2) House	(3) Farm	(4) Assets	(5) Income	(6) Debt	(7) Sick
α_0	2.304**	1.238***	1.654***	1.230***	1.659***	1.000***	1.299***
	(0.825)	(0.181)	(0.392)	(0.168)	(0.355)	(0.240)	(0.166)
μ_0	0.569***	0.546***	0.703***	0.559***	0.743***	0.508***	0.564***
	(0.146)	(0.0686)	(0.133)	(0.0655)	(0.127)	(0.104)	(0.0626)
α_1	1.215***	1.303***	1.158***	1.481***	1.117***	1.488***	0.874+
	(0.160)	(0.319)	(0.171)	(0.443)	(0.172)	(0.211)	(0.468)
μ_1	0.543***	0.574***	0.510***	0.481***	0.479***	0.565***	0.426*
	(0.0622)	(0.125)	(0.0678)	(0.146)	(0.0690)	(0.0727)	(0.208)
μ_1	0.543***	0.574***	0.510***	0.481***	0.479***	0.565***	0.426*
	(8.74)	(4.58)	(7.52)	(3.30)	(6.95)	(7.77)	(2.04)
$\alpha_0 = \alpha_1$	0.195	0.859	0.245	0.5977	0.168	0.127	0.391
Clustered SE's	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	720	720	720	720	720	720	720

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.3 The Convex Time Budget (CTB) Experiment: Individual Results

Based on the data from the convex time budget (CTB) experiments, we can also estimate the individual-level preference parameters. The distributions of each individual preference parameter are shown in Figure 2.2 and Table 2.10. While discount factor and risk parameters are clustered, we can see variations in the present bias parameter. We also examine the relationship between each parameter and observed characteristics captured by age and education level (Figure 2.3 and Table 2.11). While the correlation is not necessarily strong, we find negative correlation between present bias or time discount factor and education level. To validate this correlation, we run a quantile regression (Figure 2.4). These correlations can be found at a rather extreme level of parameters.

Figure 2.2: The Distribution of Each Individual Deep Parameters

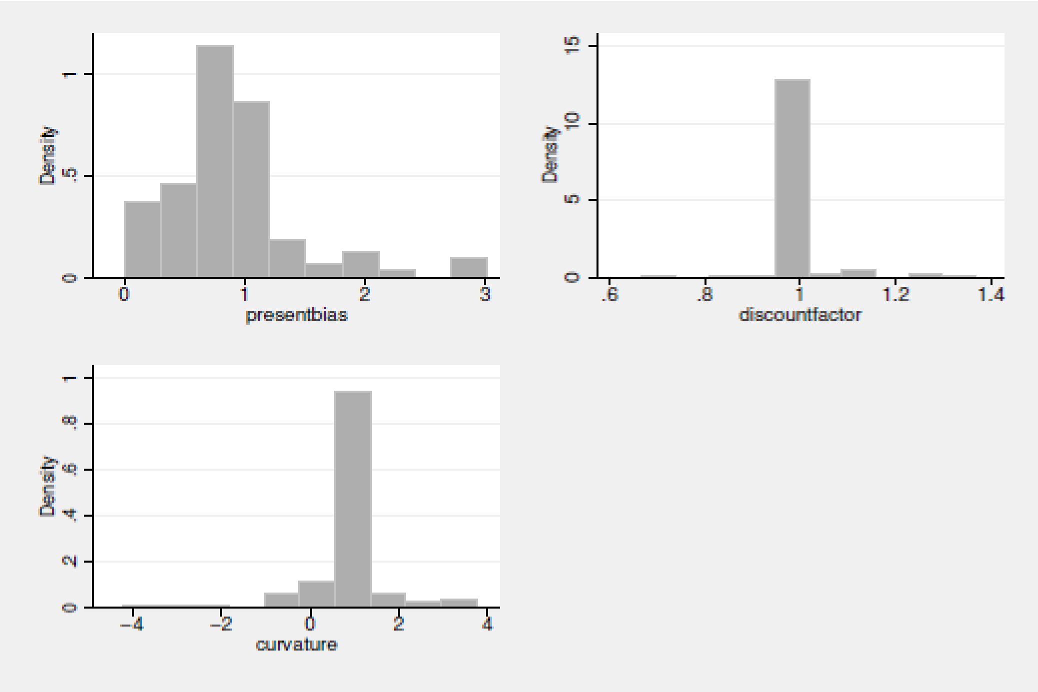


Table 2.10: The Result of Individual CTB

Statistics	Present Bias	Discount Factor	Curvature
Count	120	120	120
Mean	2.32	1.04	1.14
sd	4.34	0.13	1.38
p5	0.13	0.96	-0.50
p25	0.68	0.99	0.75
Median	0.88	0.99	0.91
p75	1.09	1.00	0.94
p95	15.20	1.39	4.36

Figure 2.3: The Relationship between Deep Parameters, Age and Education

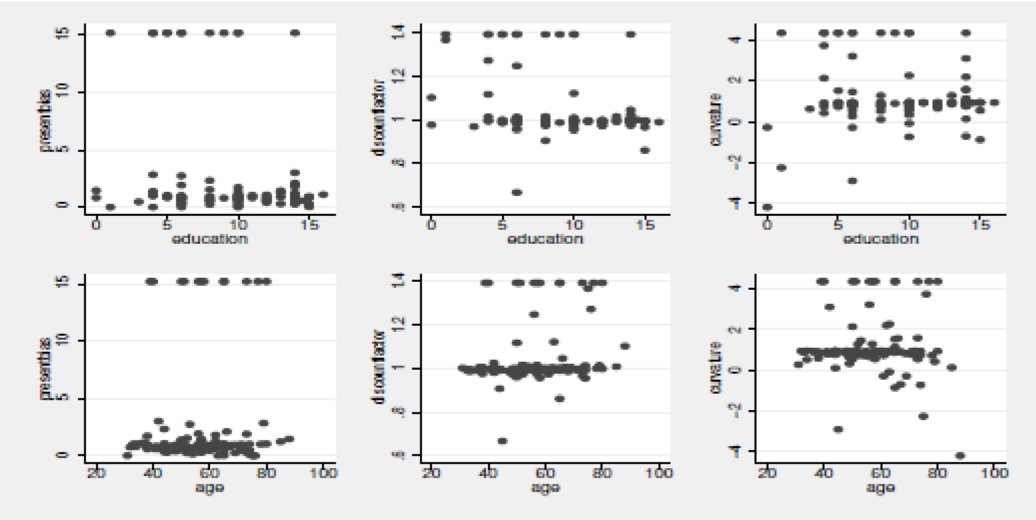


Table 2.11: OLS Regression

	(1) presentbias	(2) discountfactor	(3) curvature
age	-0.000268	0.00108*	-0.0101
	(0.00471)	(0.000515)	(0.00953)
education	0.00538	-0.00335	0.0462
	(0.0144)	(0.00224)	(0.0329)
_cons	0.856**	0.973***	0.895+
	(0.294)	(0.0340)	(0.453)
N	108	108	108

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.4: The Quantile Regression

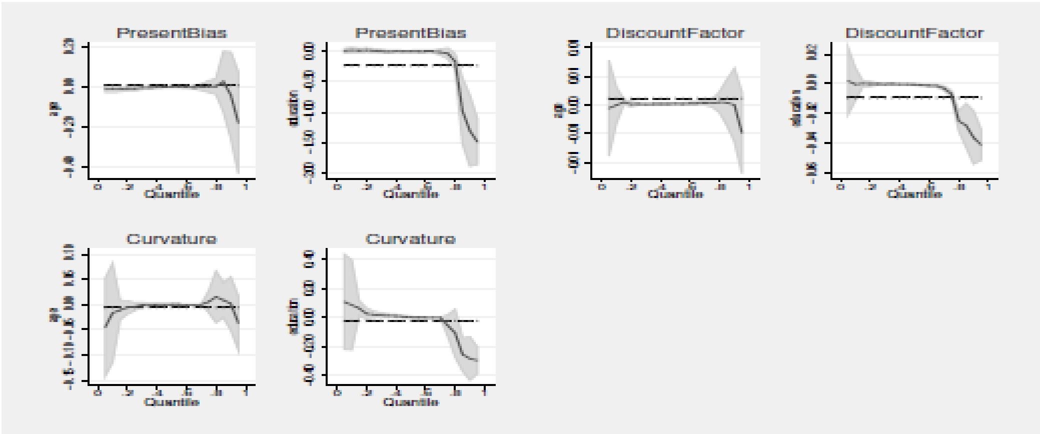
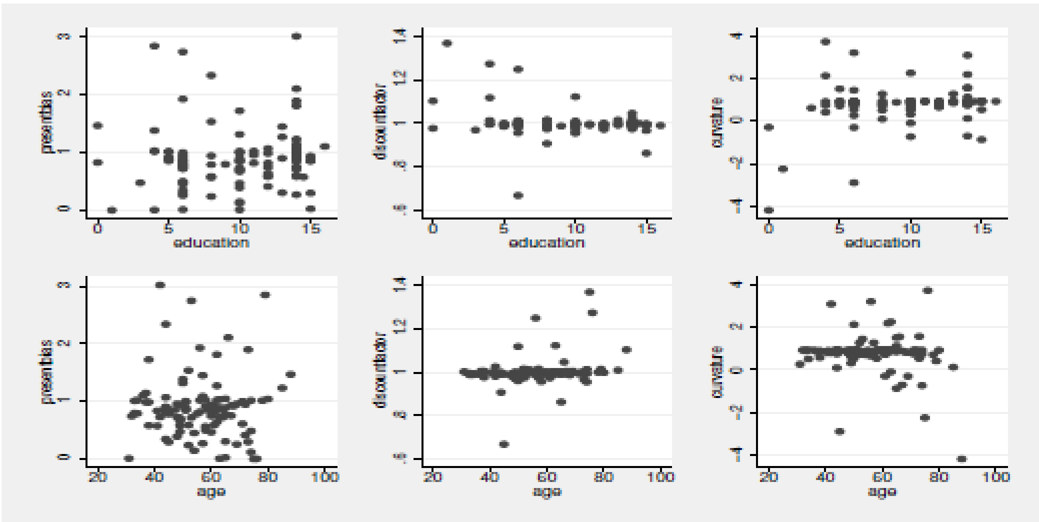


Figure 2.5: The Relationship between Deep Parameters, Age and Education without Outliers



We replicated the same analysis using a trimmed sample by deleting observations with the largest present bias parameter (Table 2.12). The results, shown in Table 2.13 and Figure 2.6, maintain the same qualitative pattern as before.

Table 2.12: The Result in Individual CTB without Outliers

Statistics	Present Bias	Discount Factor	Curvature
Count	108	108	108
Mean	0.893	1.000	0.782
sd	0.540	0.066	0.916
p5	0.119	0.960	-0.704
p25	0.599	0.990	0.745
Median	0.855	0.994	0.899
p75	1.017	1.001	0.938
p95	1.929	1.102	2.137

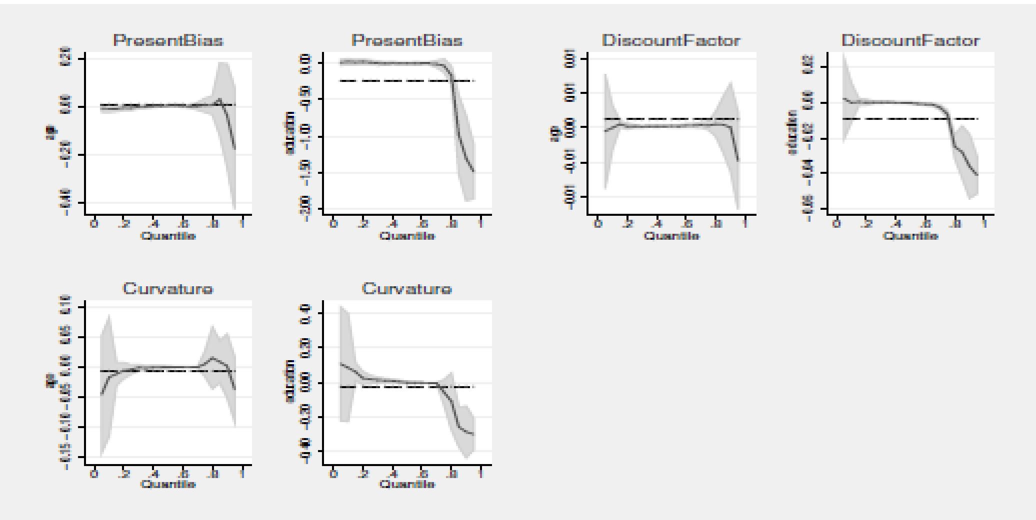
Table 2.13: OLS Regression without Outliers

	(1) presentbias	(2) discountfactor	(3) curvature
age	-0.000268	0.00108^{*}	-0.0101
	(0.00471)	(0.000515)	(0.00953)
education	0.00538	-0.00335	0.0462
	(0.0144)	(0.00224)	(0.0329)
_cons	0.856^{**}	0.973^{***}	0.895^{+}
	(0.294)	(0.0340)	(0.453)
N	108	108	108

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.6: The Quantile Regression without Outliers



4.4 Dictator Game Results

In addition to the CTB and the DMPL experiments, we conduct a canonical dictator game experiment to elicit altruism. In the dictator game, the sender, called the "dictator," is provided with PhP 1,000 in 100 peso notes as the initial endowment that he/she can either keep or allocate to the receiver. Hence, the dictator must decide the transfer amount to his receiver from the possible transfer amounts, 0, 100, 200, 300, 400, 500, 600, 700, 800, 900, and 1,000 pesos. Since there is no self-interested reason for the sender to transfer money, the senders with zero transfers satisfy the Nash equilibrium. Hence, the actual positive amount of transfer is interpreted as the level of altruism (Camerer and Fehr, 2004; Levitt and List, 2007). We also adopt strategy methods, asking all participants as a sender the amounts they would send to each of four potential partners. The four partners are a randomly selected person in the same barangay, a randomly selected victim of the typhoon Yolanda, a randomly selected victim of the Great East Japan Earthquake of March 2011 and a randomly selected person from the Philippines. To investigate how the partner affects the subjects' responses and Habagat changes their responses, we postulate the following regression equation

$$Donation_{ij} = \beta_0 + \beta_1 Partner_{ij} + \beta_2 Habagat_i + \beta_3 Partner_{ij} \times Habagat_i + \beta_4 X_i + \varepsilon_{ij} \tag{13}$$

where $Donation_{ij}$ is the amount subject *i* gives to the partner *j* in the dictator game, $Partner_{ij}$ is a dummy variable which indicates who is the partner, $Habagat_i$ is a dummy variable which indicates whether the subject is affected by Habagat or not, X_{ij} is a control variable and ε_{ij} is an error term.

Histograms of the dictator game results are shown in Figure 2.7 by partner. The amounts sent to victims of typhoon Yolanda or the Great East Japan Earthquake are significantly larger than those sent to someone in the same village or in the Philippines. The same pattern is confirmed by the regression results of Table 2.14 and 2.15.

Figure 2.7: The Histogram of the Amount of Donation

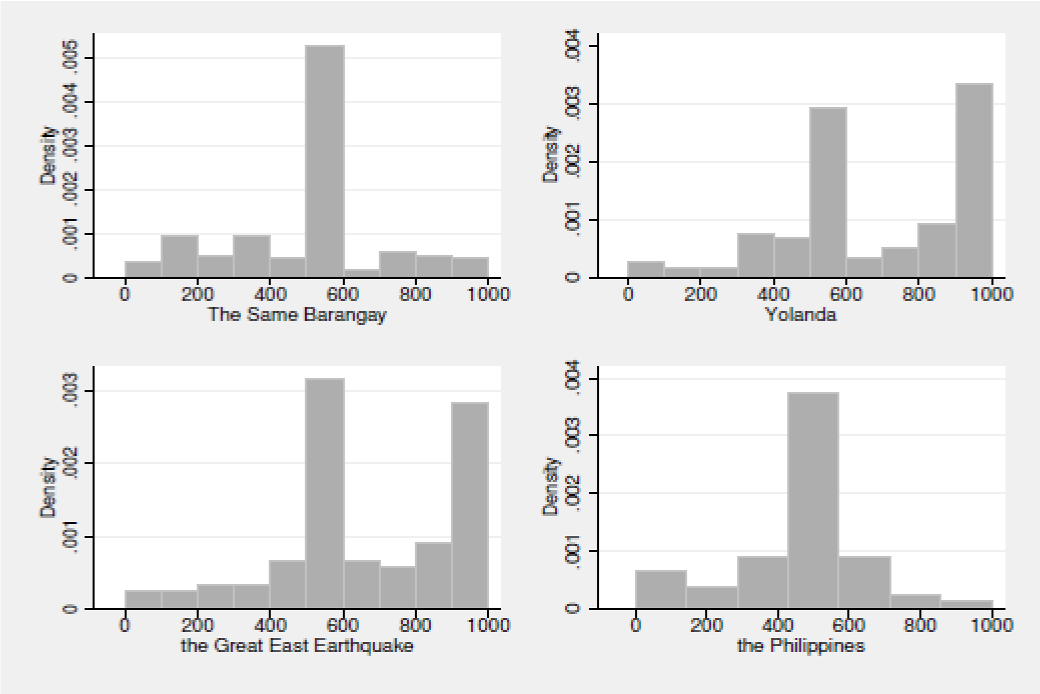


Table 2.14: The Relationship between the Amount of Donation, the Partner and Habagat

	(1) donation	(2) donation	(3) donation	(4) donation	(5) donation
Yolanda	195.8***	213.5***	213.5***	213.5***	145.7
	(27.99)	(31.97)	(32.03)	(32.30)	(100.5)
Earthquake	176.7***	187.6***	187.6***	187.6***	230.4*
	(27.77)	(33.48)	(33.53)	(33.82)	(95.18)
Philippines	-2.778	11.98	11.66	2.946	115.9+
	(25.30)	(24.77)	(24.75)	(24.64)	(62.63)
gender		-41.97	-40.06	-50.89	-52.83
		(48.88)	(49.73)	(52.08)	(53.09)
age		6.870	7.469	11.45	11.06
		(11.60)	(12.01)	(11.39)	(11.90)
age2		-0.0233	-0.0291	-0.0610	-0.0581
		(0.0954)	(0.0994)	(0.0941)	(0.0990)
education		10.91*	10.60+	9.942+	10.11+
		(5.156)	(5.350)	(5.501)	(5.657)
None			-24.83		
			(89.64)		
House				-6.017	4.678
				(47.35)	(61.42)
Farm				9.752	0.308
				(47.30)	(63.87)
Assets				-123.8	-21.41
				(83.97)	(135.3)
Income				52.74	47.28
				(43.11)	(52.43)
Debt				-9.620	9.281
				(43.09)	(56.69)
Sick				-18.28	-30.92
				(77.51)	(83.90)

Table 2.14: (*cont.*)

House × Yolanda					-16.24
					(72.77)
House × Earthquake					-37.03
					(89.47)
House × Philippines					15.50
					(57.36)
Farm × Yolanda					75.54
					(81.98)
Farm × Earthquake					1.740
					(84.48)
Farm × Philippines					-89.12
					(58.33)
Assets × Yolanda					-181.2
					(181.2)
Assets × Earthquake					-195.0
					(202.5)
Assets × Philippines					170.2^{+}
					(98.18)
Income × Yolanda					66.37
					(69.88)
Income × Earthquake					-10.18
					(72.77)
Income × Philippines					-82.95
					(56.56)
Debt × Yolanda					-18.72
					(72.45)
Debt × Earthquake					-40.48
					(76.78)
Debt × Philippines					9.602
					(61.70)
Sick × Yolanda					-80.61
					(108.8)

Table 2.14: (*cont.*)

Sick × Earthquake					85.53
					(109.5)
Sick × Philippines					53.80
					(78.24)
_cons	458.3***	32.29	43.86	-114.2	-111.0
	(20.00)	(353.2)	(356.2)	(363.0)	(373.3)
N	414	307	307	307	307

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.15: The Relationship between the Amount of Donation, the Deep Parameters, the Partner and Habagat

	(1) donation	(2) donation	(3) donation	(4) donation	(5) donation
presentbias	-12.43^{+}	-9.036	-9.076	-7.359	-9.482
	(6.614)	(8.642)	(8.649)	(9.236)	(8.650)
curvature	9.596	4.993	5.128	2.432	5.534
	(16.62)	(19.14)	(18.75)	(20.97)	(20.29)
discountfactor	356.4*	385.8^{+}	386.4^{+}	337.5	384.8
	(145.1)	(217.3)	(217.5)	(255.6)	(250.4)
Yolanda	213.5***	213.5***	213.5***	213.5***	145.7
	(31.92)	(32.14)	(32.19)	(32.47)	(101.0)
Earthquake	187.6***	187.6***	187.6***	187.6***	230.4*
	(33.42)	(33.65)	(33.70)	(33.99)	(95.71)
Philippines	6.956	13.10	12.76	5.490	125.2^{+}
	(27.25)	(25.05)	(25.06)	(24.63)	(64.88)
gender		-50.99	-48.89	-50.12	-52.83
		(49.58)	(50.37)	(52.57)	(53.63)
age		6.248	6.900	11.01	9.993
		(11.92)	(12.35)	(11.92)	(12.38)
age2		-0.0217	-0.0280	-0.0611	-0.0531
		(0.0989)	(0.103)	(0.0994)	(0.103)
education		12.65*	12.30*	11.38^{+}	11.54^{+}
		(6.002)	(6.143)	(6.114)	(6.253)
None			-28.00		
			(90.93)		
				-13.27	-1.671
House				(49.42)	(65.19)
Farm				8.266	-0.926
				(47.95)	(66.25)
Assets				-81.77	21.39
				(94.06)	(146.0)

Table 2.15: (*cont.*)

Income	47.95	42.31
	(44.03)	(54.96)
Debt	-25.41	-7.988
	(45.42)	(59.13)
Sick	-27.44	-40.27
	(78.22)	(88.94)
House × Yolanda		-16.24
		(73.17)
House × Earthquake		-37.03
		(89.96)
House × Philippines		11.30
		(57.89)
Farm × Yolanda		75.54
		(82.43)
Farm × Earthquake		1.740
		(84.95)
Farm × Philippines		-95.66
		(60.51)
Assets × Yolanda		-181.2
		(182.2)
Assets × Earthquake		-195.0
		(203.6)
Assets × Philippines		224.3^{+}
		(127.3)
Income × Yolanda		66.37
		(70.27)
Income × Earthquake		-10.18
		(73.18)
Income × Philippines		-84.71
		(57.44)
Debt × Yolanda		-18.72
		(72.85)

Table 2.15: (*cont.*)

Debt × Earthquake					-40.48
					(77.20)
Debt × Philippines					8.979
					(62.33)
Sick × Yolanda					-80.61
					(109.4)
Sick × Earthquake					85.53
					(110.1)
Sick × Philippines					48.23
					(81.45)
_cons	85.11	-339.0	-326.0	-429.0	-454.6
	(152.7)	(415.5)	(416.5)	(437.6)	(433.7)
N	307	307	307	307	307

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.5. Behaviours

In previous studies on behavioural economics, researchers attributed undesirable behaviours such as obesity, over-eating, debt overhang, gambling, smoking, drinking, and other procrastination behaviours to naive hyperbolic discounting (Banerjee and Mullainathan, 2010). In our data, we can verify whether and how individual preferences are related with risk taking behaviour such as gambling, smoking, and drinking. The estimation results are shown in Table 2.16, which represents insignificant relationship between the present bias parameter and risk taking behaviours.

Table 2.16: The Relationship between Risk Taking Behavior and Deep Parameters

	(1) #ofgambling	(2) #ofgambling	(3) smoking	(4) smoking	(5) alcohol	(6) alcohol
presentbias (β)	0.0470	0.0376	-0.00530	0.00557	-0.0246	-0.0114
	(0.0297)	(0.0284)	(0.0231)	(0.0213)	(0.0183)	(0.0165)
discountfactor (δ)	-2.187**	-1.964*	0.0641	-0.187	1.258**	0.0779
	(0.685)	(0.808)	(0.894)	(0.845)	(0.420)	(0.581)
curvature (α)	0.0199	0.0341	0.0117	-0.00588	-0.0409	0.0125
	(0.0602)	(0.0670)	(0.0580)	(0.0559)	(0.0347)	(0.0547)
gender		-0.393*		0.371***		0.517***
		(0.164)		(0.0568)		(0.0759)
age		0.0000458		0.0199		-0.0285
		(0.0427)		(0.0259)		(0.0279)
age2		0.000000240		-0.000153		0.000316
		(0.000366)		(0.000229)		(0.000249)
education		-0.00295		0.00367		-0.0114
		(0.0215)		(0.0106)		(0.0108)
_cons	2.876***	2.799+	0.682	0.172	-0.680	0.956
	(0.690)	(1.613)	(0.859)	(1.203)	(0.424)	(1.043)
N	120	120	120	120	120	120

Standard errors in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5. Conclusion

This paper's empirical investigations provide three main results. First, the Convex Time Budget (CTB) experiments developed by Andreoni and Sprenger provide reasonable levels of present bias, time discounting and risk aversion parameters in all specifications. Second, in contrast with Andreoni and Sprenger's findings in the United States, we find that the estimated present bias parameter falls significantly below one in the Filipino village we studied, indicating quasi-hyperbolic discounting in the whole sample. This finding indicates that Andreoni and Sprenger's argument that the unique steps CTB experiments take to equate the costs and risks associated with payments that are made too soon and payments that are made too late may not be related to the dynamically consistent time preferences they obtain. Finally, we divide our sample into sub-groups depending on their damage types. By doing this, we find that the natural disaster affects the present bias parameter: being hit by the flood makes individuals significantly more present-biased than those who are unaffected by the flood. This implies that individual preference parameters are not constant over time and that they change under some circumstances.

These findings come with several important caveats. First, while we find that the natural disaster affects the present bias parameter, the mechanisms behind such affects are still unknown from the theoretical viewpoints. Second, since the relationship between preference parameters and real-world socio-economic circumstances are under-investigated, we should link and analyse living standard surveys and experimental responses by the same individuals. These are important tasks for future research.

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CHAPTER 3

The Effects of Natural Disasters on Households' Preferences and Behaviours: Evidence from Thai Farmers during and after the 2011 Mega Flood

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This paper studies the consequences of the 2011 mega flood in Thailand on subjective expectations, preferences, and behaviours of Thai farming households affected by the disaster. First, we found that the flood seemed to make households adjust upward their subjective expectations of future flood events and of possible damage caused by future floods. The flood also affected the expectations of households regarding government assistance. However, we found no evidence of moral hazard arising from the government's implicit insurance through disaster assistance. Second, the 2011 mega flood was positively associated with higher risk aversion and more risk averse households were more likely to adopt strategies that mitigate the severity and the damage of future floods. Finally, we found that the households that were directly hit by the flood seemed to be less altruistic. These findings shed light on the credibility of government assistance in the aftermath of widespread natural disasters and the role of governments and insurance markets in future natural disaster risk management.

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1. Introduction

Natural disasters have crucial implications for economic development. Not only do they generally cause damage to an economy's physical and human capital as well as its institutions, disasters can also lead to changes in people's behaviour.[1] Largely unexpected and severe disasters could induce a revision of subjective expectation of risk exposure by affected households. Experiencing or observing disasters may also alter the risk, time, and social preferences of households and these may in turn result in changes in their behavioural choices.

Several recent studies have shown empirical evidence that disasters can cause changes in risk, time, and social preferences. Regarding risk preference, Eckel, *et al.* (2009) found that experiencing hurricane Katrina affected risk preferences of the hurricane evacuees. Cameron and Shah (2012) found that individuals who had recently suffered a flood or earthquake in Indonesia exhibited greater risk aversion than individuals living in similar but unaffected villages. Cassar, *et al.* (2011) showed that the 2004 Indian Ocean tsunami in Thailand resulted in higher risk aversion. Page, *et al.* (2012) studied the 2011 Brisbane flood in Australia and found that after a large negative wealth shock, those directly affected became more willing to adopt riskier options in their decision-making process. Regarding time preference, Callen (2011) showed that exposure to the Indian Ocean Earthquake tsunami affected a patience measure in a sample of Sri Lankan wage workers. Regarding social preference, Castillo and Carter (2011) found that the large negative shock caused by Hurricane Mitch in 1998 affected altruism, trust, and reciprocity in small Honduran communities. Research undertaken by from Cassar, *et al.* (2011) showed that the 2004 Indian Ocean tsunami in Thailand also resulted in higher altruism.[2]

Such changes in risk, time, and social preferences could affect household behaviours in various ways. For example, an increase in risk aversion could induce households to invest in more conservative projects while an increase in risk tolerant behaviour may induce a higher demand for gambling and risky

[1] For a survey of literature on the effects of natural disasters on the economy, see Samphantharak (2014).

[2] There is also literature on the effects of traumatic and catastrophic civil conflicts on preferences. For example, see Voors, *et al.* (2012); Cassar, *et al.* (2013); and Callen, *et al.* (2013).

behaviours or more aggressive investment in risky ventures. A change in time preference could affect intertemporal decisions of households, such as savings. Likewise, an increase in altruism may lead to a reduction in public goods exploitation. Most importantly, for poor households in developing economies, changes in preferences may have significant impacts on their safety nets. As Sawada (2014) summarised, various mechanisms provide strategies for households to manage or cope with natural disaster risks. The first mechanism is household-level strategies, which include self-insurance through savings and consumption reallocation, as well as diversification of household income. The second mechanism is market-based strategies through credit and insurance contracts. The third mechanism is insurance against risk through community, including informal assistance among family members and friends. And finally, the fourth mechanism is public assistance from the government. On the one hand, behavioural changes induced by changes in preferences following natural disasters can induce households to engage in various mechanisms. For example, increasing risk aversion may lead to a reduction in risk behaviours and higher demand for insurance. Similarly, increasing patience could cause an increase in savings and increasing altruism could enhance social risk sharing. On the other hand, as in any insurance arrangement, disaster safety nets could also create moral hazard. For example, public disaster relief may lead to excessive risk taking and crowd out demand for self insurance or private insurance. In such cases, the government's provision of safety nets serves as a substitute for private insurance rather than as a complement.

This paper aims to contribute to this growing literature by studying the consequences of the 2011 mega flood in Thailand on the subjective expectations, preferences, and behaviours of Thai farming households affected by the disaster. Understanding these consequences has crucial policy implications regarding risk management and risk coping strategies of agricultural households in a rural economy. Like other East Asian countries, natural disasters are common in Thailand. Due to the country's location in the tropic, the most common natural disasters experienced in Thailand have been floods. According to the Emergency Events Database (EM-DAT), Thailand experienced 59 flood events during 1980-2010, averaging approximately two events per year. Although floods occurred frequently during this period, they did not generally result in high numbers of people killed, with the cumulative death toll from all flood events during 1980-2010 less than one death per flood event on average.[3] In most cases, the damage was also geographically limited, with the exception of severe floods. The most recent one was the mega flood of 2011, one of the deadliest and most destructive natural disasters in Thailand's history.

The 2011 mega flood was the largest flood to hit Thailand in over half a century. It eventually claimed over 800 lives, making it the second deadliest natural disaster in Thailand's recent history, only ranked behind the 2004 Indian Ocean Tsunami. The flood was initially caused by a series of heavy rains combined with multiple tropical storms that began in May and lasted through October. Excessive rainwater eventually exceeded the capacity of the country's key dams and drainage systems, causing rapid downstream flows from the north to the central plain. The flood affected 12.8 million people, 19,376 ha of agricultural land, and 9,859 factories. In total, the flood covered approximately one-third of Thailand, affecting 66 out of 77 provinces in all regions of the country. It affected the agricultural sector in at least 26 provinces in the northern, central, and northeastern regions (World Bank 2012). In particular, the flood inundated the key rice growing areas in the Chao Phraya and Thachin river basins. The Thai government spent more than USD 3 billion on relief, of which approximately 8 percent went to rice farmers. The total loss and damage was estimated at USD 46.5 billion, or 14 percent of gross domestic product (GDP).

Given its rarity and severity, the 2011 mega flood serves as an ideal natural experiment for a study of how households cope with a largely unexpected natural disaster and how the disaster affects households' preferences and behaviours. Although the 2011 mega flood also affected industrial areas, this study will focus only on the effects of the flood on rice farming households, because most of the areas directly affected by the flood were farmland, especially for rice cultivation, and these farms were operated by relatively poor households whose access to risk management and risk coping mechanisms was limited. The flood, therefore, impacted the livelihood of many farming households in a substantial way and had crucial policy implications regarding

[3] These statistics are based on the Emergency Events Database (EM-DAT), one of the most comprehensive databases on disasters maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Louvain in Belgium. For a more detailed discussion on the impact of the 2011 mega flood on the Thai economy, see Samphantharak (2014).

safety nets of poor and vulnerable households.[4] To achieve the goals of this study, we will first explore how farming households in Thailand coped with the mega flood in 2011. Second, we will study how the flood affected the subjective expectations of Thai farmers regarding future flood events, flood damage, and disaster relief provided by the government and the community. Third, we will explore how experiencing the flood affected risk, time, and social preferences of farming households. Finally, the study will analyse how households prepare themselves for possible future flood events, and whether the expectation of public assistance crowds out private efforts in disaster prevention and insurance. We conclude the paper with policy implications regarding the roles of household, market, community, and government on natural disaster risk management and risk coping strategies.

2. Data

The data used in this study are from a recent survey of rice farming households in Thailand. The survey was conducted between January and April 2014 in four provinces: Pitsanulok in the northern region, Suphanburi in the central region, and Khonkaen and Nakorn Ratchasima in the northeastern region. For each province, two additional stratifications were used in our sampling strategy: (1) whether the farm was flooded in 2011 and (2) whether the farm was generally prone to floods in normal years. First, we utilised the discontinuity generated by the 2011 flood to construct a variation in flood experience. This discontinuity allowed us to compare farmers who were directly hit by the flood with those who did not directly experience the flood. A satellite map of the 2011 flood was used to initially identify flooded areas. Phone calls to village heads and subsequent field visits further allowed us to identify flooded and non-flooded households.[5] Second, we identified flood-prone farms as those

[4] In a recent study, Poaponsakorn and Meethom (2012) compared household data from Thailand's socioeconomic surveys in 2009 and 2011 and mapped them with the flooded areas by using satellite images. They showed that the 2011 mega flood in Thailand had a large negative impact on farm profits of some middle-income households in the flooded provinces.

[5] It is important to note that most, if not all, households in Thailand were affected by the 2011 mega flood in one way or another. Even the households that were not directly hit by the flood were affected indirectly. In this sense, it is unavoidable that there were spillover effects on the non-flooded households. These effects include, but are not limited to, new information about the flood and the management of flood by the government perceived by the farmers. Disruptions of local, regional, and national economic activities affected prices

who had been flooded more than three times in the past five years. Our sample contains a total of 426 sampled households. The sample size for each of the sampling categories by province is shown in Table 3.1. Note that, although we originally intended to collect balanced samples for all categories, the sample size was largely unbalanced for Pitsanulok (97 flooded farms versus 25 non-flooded farms) since the majority of rice farms in the province were flooded in 2011. For the other three provinces, the numbers of flooded and non-flooded farms were relatively similar.

Table 3.1: Sample Size of the Survey

Suphanburi

		Flood Prone		Total
		No	Yes	
2011 Mega	No	38	10	48
Flood	Yes	32	24	56
Total		70	34	104

Pitsanulok

		Flood Prone		Total
		No	Yes	
2011 Mega	No	15	10	25
Flood	Yes	54	43	97
Total		69	53	122

Khonkaen

		Flood Prone		Total
		No	Yes	
2011 Mega	No	47	3	50
Flood	Yes	35	19	54
Total		82	22	104

Nakorn Ratchasima

		Flood Prone		Total
		No	Yes	
2011 Mega	No	37	13	50
Flood	Yes	29	17	46
Total		66	30	96

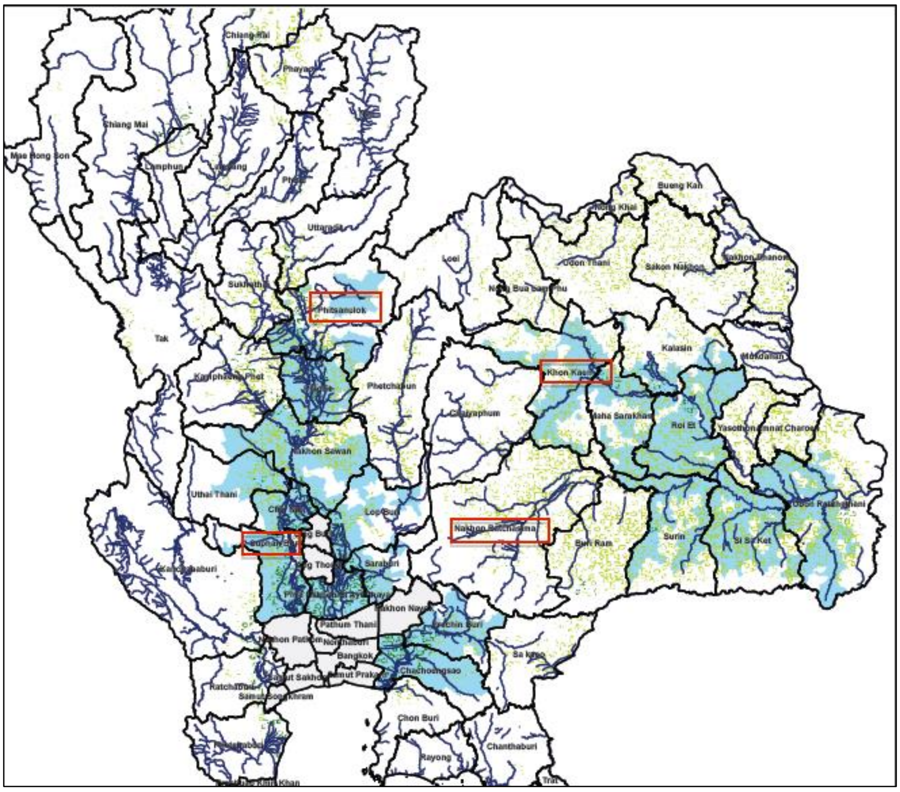
The four provinces were intentionally selected to provide variations in the nature of flood exposure and severity of flooding. As shown in Figure 3.1, Suphanburi and Pitsanolok are located in the Chao Phraya and Thachin River Basin Group while Khonkaen and Nakorn Ratchasima are in the Mekong Tributary Basin Group.[6] Within the Chao Phraya-Thachin River Basin Group, Pitsanulok is located upstream in the Nan River Basin while Suphanburi is located downstream in the Thachin River Basin. In the northeast, Khonkaen is located in the upstream area of the Chi River Basin while Nakorn Ratchasima is in the upstream area of the Mun River Basin. Both the Chi and the Mun Rivers flow into the Mekong River. As summarised in Table 3.2, the 2011 flood

of goods and services as well as incomes of many households in the non-flood areas. The effects, however, should bias our results toward finding no differences of preferences and behaviours between the farmers who were directly hit by the flood and the similar farmers whose farms were not flooded.

[6] Based on the classification of Thailand's National Committee on Hydrology, there are 25 distinct hydrological units, or basins, in Thailand. The basins are then regrouped into nine basin groups. The Chao Phraya-Thachin River Basin Group consists of the basins of the rivers Ping, Wang, Yom, Nan, Chao Phraya, Sakae Krung, Pasak, and Thachin. The Mekong Tributary Basin Group consists of the basins of the rivers Mekong, Kok, Chi, Mun and the Tonle Sap.

hit upstream Pitsanulok earlier (around July-August) while downstream Suphanburi experienced the flood more than a month later (around September). The flood in Pitsanulok lasted for 81 days on average whereas it lasted for 97 days in Suphanburi (although the median flood days were 90 for both provinces). Anticipating the floodwater flowing down, farmers in Suphanburi in principle had more time to prepare and cope with the disaster than those in Pitsanulok. However, revenue losses from the 2011 flood were similar in both provinces, averaging 182,000 baht per household (the median revenue loss was slightly higher in Pitsanulok, at 136,800 baht, as compared with Suphanburi, at 118,752 baht). Finally, the nature of the flood in the northeast was different from the Chaophraya-Thachin area. Both Khonkaen and Nakorn Ratchasima experienced the flood later, in October. The duration of the flood for both provinces was also shorter, averaging 45-47 days. Consequently, the damage from the flood in terms of revenue loss was smaller, amounting to an average of 77,249 baht for Khonkaen and 101,615 baht for Nakorn Ratchasima.[7]

Figure 3.1: Map of Studied Provinces



7 The exchange rate during the time of the survey was approximately 32 baht per US dollar.

Table 3.2: Characteristics of the 2011 Mega Flood by Province

Variable	No. Obs.	Mean	Std. Dev.	Min	Median	Max	No. Obs.	Mean	Std. Dev.	Min	Median	Max
	Suphanburi						*Pitsanulok*					
Starting Month	56	9,02	0,13	9	9	10	97	7,67	1,08	5	8	9
Flood Length (Days)	56	97,41	44,30	10	90	180	97	80,88	39,84	15	90	180
Loss Revenue (Baht)	54	182.515	160.330	16.000	118.752	696.800	97	182.056	148.321	9.720	136.800	800.400
	Khonkaen						*Nakorn Ratchasima*					
Starting Month	54	9,59	0,86	8	10	12	46	9,89	0,71	7	10	11
Flood Length (Days)	54	45,28	22,11	10	45	90	46	46,93	26,93	14	37,5	120
Loss Revenue (Baht)	54	77.249	75.067	3.000	54.300	360.586	46	101.615	133.835	3.500	55.438	763.200

Table 3.3A presents descriptive statistics for farming households in our sample by province. The sampled households in all four provinces shared similar demographic characteristics at the time of the survey in early 2014. The average household size was four persons, with two male and two female members. Three of the four were of working age (15-60 years old) and two of the three were involved in rice farming. Slightly more than half (54-57 percent) of the households in our sample had a male head. The highest education attainment of the majority of the household heads was primary education, ranging from 75 percent in Pitsanulok to 88 percent in Khonkaen. The main differences between households across the four provinces were their occupations, income, and wealth. While households in Suphanburi and Pitsanulok heavily relied on rice farming (the percentage of household revenue from rice farming out of total revenue was 75 percent for the average household in Suphanburi and 86 percent in Pitsanulok), rice revenue contributed to less than half of total household revenue for the sampled households in the northeast (27 percent in Khonkaen and 42 percent in Nakorn Ratchasima). The households in the northeast were also poorer on average—total household income was only 95,967 baht for the median household in Khonkaen and 166,200 baht for Nakorn Ratchasima, while it was 368,000 baht for Suphanburi and 304,600 baht for Pitsanulok. Alternatively, Table 3.3B presents similar descriptive statistics for non-flooded and flooded farming households in our sample. The table shows that, on average, non-flooded and flooded households have similar demographic characteristics. The medians for almost all demographic variables for these two groups are the same. For income and asset variables, all of the means for these two groups were statistically no different

from each other with traditional levels of significance, mainly due to their large standard deviation.

Table 3.3A: Descriptive Statistics of Households by Province (as of 2014)

Variable	No. Obs.	Mean	Std. Dev.	Min	Median	Max	No. Obs.	Mean	Std. Dev.	Min	Median	Max
			Suphanburi						*Pitsanulok*			
Household size, total	104	4,25	1,93	1	4	11	122	4,06	1,44	1	4	8
Household size, male	104	2,06	1,30	0	2	7	122	1,98	1,11	0	2	5
Household size, female	104	2,19	1,22	0	2	7	122	2,08	0,97	0	2	5
Household size, 15-60	104	2,86	1,40	0	3	6	122	2,84	1,26	0	3	6
Household size, rice farmers	104	2,13	1,16	1	2	6	122	2,35	0,90	1	2	5
Household head = Male	104	0,67	0,47	0	1	1	122	0,70	0,46	0	1	1
Household head's age	104	54,44	10,58	27	56	81	122	53,73	9,25	36	53	83
Household head's education = Primary	104	0,81	0,40	0	1	1	122	0,75	0,44	0	1	1
Household head's education = Secondary	104	0,14	0,35	0	0	1	122	0,16	0,36	0	0	1
Household head's education = Vocational	104	0,02	0,14	0	0	1	122	0,07	0,26	0	0	1
Household head's education = Higher	104	0,03	0,17	0	0	1	122	0,02	0,16	0	0	1
Household revenue, rice	104	553.690	479.190	50.000	451.500	3.000.000	122	470.354	303.322	47.100	400.000	1.561.200
Household revenue, agricultural nonrice	104	157.216	582.954	0,00	0,00	5.500.000	122	12.798	75.379	0	0	800.000
Household revenue, nonagriculture	104	83.798	166.861	0,00	7200,00	1.285.000	122	73.992	169.301	0	19.100	1.440.000
Household revenue, rice (% of total revenue)	104	75,12	25,65	3,64	81,56	100,00	122	85,57	17,97	30,00	92,55	100,00
Household cost, rice	104	213.902	181.044	21000,00	150000,00	1.000.000	122	190.830	153.478	12.000	150.000	792.000
Household cost, agricultural nonrice	104	56.888	237.592	0,00	0,00	2.200.000	122	3.582	19.409	0	0	200.000
Household cost, nonagriculture	104	21.042	116.144	0,00	0,00	1.095.000	122	15.467	101.536	0	0	1.080.000
Household income, rice	104	339.789	338.442	24000,00	232500,00	2.000.000	122	279.524	187.756	-190.000	251.300	850.200
Household income, agricultural nonrice	104	100.328	358.248	-10000,00	0,00	3.300.000	122	9.216	56.459	0	0	600.000
Household income, nonagriculture	104	62.756	100.080	0,00	7200,00	420.000	122	58.525	100.844	0	17.900	786.000
Household income, total (baht)	104	502.872	506.202	44000,00	368600,00	3.428.000	122	347.265	230.624	-190.000	304.600	1.186.000
Household assets (baht)	104	1.032.724	1.541.448	24200,00	611965,00	11.500.000	122	850.952	1.008.671	48.350	690.600	9.195.000
			Khonkaen						*Nakorn Ratchasima*			
Household size, total	104	4,25	1,93	1	4	11	122	4,06	1,44	1	4	8
Household size, male	104	2,06	1,30	0	2	7	122	1,98	1,11	0	2	5
Household size, female	104	2,19	1,22	0	2	7	122	2,08	0,97	0	2	5
Household size, 15-60	104	2,86	1,40	0	3	6	122	2,84	1,26	0	3	6
Household size, rice farmers	104	2,13	1,16	1	2	6	122	2,35	0,90	1	2	5
Household head = Male	104	0,67	0,47	0	1	1	122	0,70	0,46	0	1	1
Household head's age	104	54,44	10,58	27	56	81	122	53,73	9,25	36	53	83
Household head's education = Primary	104	0,81	0,40	0	1	1	122	0,75	0,44	0	1	1
Household head's education = Secondary	104	0,14	0,35	0	0	1	122	0,16	0,36	0	0	1
Household head's education = Vocational	104	0,02	0,14	0	0	1	122	0,07	0,26	0	0	1
Household head's education = Higher	104	0,03	0,17	0	0	1	122	0,02	0,16	0	0	1
Household revenue, rice	104	553.690	479.190	50.000	451.500	3.000.000	122	470.354	303.322	47.100	400.000	1.561.200
Household revenue, agricultural nonrice	104	157.216	582.954	0	0	5.500.000	122	12.798	75.379	0	0	800.000
Household revenue, nonagriculture	104	83.798	166.861	0	7.200	1.285.000	122	73.992	169.301	0	19.100	1.440.000
Household revenue, rice (% of total revenue)	104	75,12	25,65	3,64	81,56	100,00	122	85,57	17,97	30,00	92,55	100,00
Household cost, rice	104	213.902	181.044	21.000	150.000	1.000.000	122	190.830	153.478	12.000	150.000	792.000
Household cost, agricultural nonrice	104	56.888	237.592	0	0	2.200.000	122	3.582	19.409	0	0	200.000
Household cost, nonagriculture	104	21.042	116.144	0	0	1.095.000	122	15.467	101.536	0	0	1.080.000
Household income, rice	104	339.789	338.442	24.000	232.500	2.000.000	122	279.524	187.756	-190.000	251.300	850.200
Household income, agricultural nonrice	104	100.328	358.248	-10.000	0	3.300.000	122	9.216	56.459	0	0	600.000
Household income, nonagriculture	104	62.756	100.080	0	7.200	420.000	122	58.525	100.844	0	17.900	786.000
Household income, total (baht)	104	502.872	506.202	44.000	368.600	3.428.000	122	347.265	230.624	-190.000	304.600	1.186.000
Household assets (baht)	104	1.032.724	1.541.448	24.200	611.965	11.500.000	122	850.952	1.008.671	48.350	690.600	9.195.000

Table 3.3B: Descriptive Statistics of Flood and Non-Flood Households (as of 2014)

Variable	No. Obs.	Mean	Std. Dev.	Min	Median	Max	No. Obs.	Mean	Std. Dev.	Min	Median	Max
	Non-Flood Households in 2011						*Flood Households in 2011*					
Household size, total	173	3,81	1,62	1	4	9	253	4,47	1,79	1	4	12
Household size, male	173	1,82	1,05	0	2	5	253	2,29	1,31	0	2	7
Household size, female	173	1,99	1,13	0	2	7	253	2,18	1,12	0	2	9
Household size, 15-60	173	2,51	1,41	0	2	6	253	3,01	1,40	0	3	10
Household size, rice farmers	173	2,08	0,90	1	2	6	253	2,32	1,03	1	2	6
Household head = Male	173	0,61	0,49	0	1	1	253	0,70	0,46	0	1	1
Household head's age	173	55,54	10,58	30	56	83	253	54,55	10,18	27	53	84
Household head's education = Primary	173	0,85	0,36	0	1	1	253	0,77	0,42	0	1	1
Household head's education = Secondary	173	0,13	0,33	0	0	1	253	0,17	0,37	0	0	1
Household head's education = Vocational	173	0,01	0,11	0	0	1	253	0,04	0,20	0	0	1
Household head's education = Higher	173	0,01	0,11	0	0	1	253	0,02	0,14	0	0	1
Household revenue, rice	173	260.311	398.987	0	115.200	3.000.000	253	350.135	339.495	0	266.400	2.000.000
Household revenue, agricultural nonrice	173	54.637	186.012	0	0	1.400.000	253	47.907	354.599	0	0	5.500.000
Household revenue, nonagriculture	173	97.590	152.598	0	43.200	1.440.000	253	116.028	245.333	0	48.000	3.010.900
Household revenue, rice (% of total revenue)	171	52,29	36,70	0	51	100	253	63,76	35,14	0	77	100
Household cost, rice	173	125.504	295.392	0	55.500	3.521.403	253	152.553	149.406	4.800	100.000	792.000
Household cost, agricultural nonrice	173	19.252	79.292	0	0	720.000	253	16.730	142.133	0	0	2.200.000
Household cost, nonagriculture	173	9.748	83.706	0	0	1.080.000	253	26.040	176.995	0	0	2.500.000
Household income, rice	173	134.806	397.189	-3.445.119	70.000	2.000.000	253	197.582	220.248	-190.000	140.000	1.300.000
Household income, agricultural nonrice	173	35.384	125.246	-36.000	0	1.000.000	253	31.177	216.760	-240.000	0	3.300.000
Household income, nonagriculture	173	87.842	111.502	0	43.200	504.400	253	89.988	131.443	-8.000	39.600	786.000
Household income, total (baht)	173	258.033	450.327	-3.324.119	176.000	2.800.000	253	318.747	314.468	-190.000	254.000	3.428.000
Household assets (baht)	173	641.287	1.021.638	20.000	374.700	11.500.000	253	843.901	1.082.638	19.000	610.000	9.358.800

3. Empirical Results

3.1. Risk Coping Activities during the 2011 Mega Flood

The first set of our empirical results focuses on how households coped with the mega flood in 2011. The survey asked each of the flooded households whether they engaged in any of the following activities: (1) selling assets; (2) reducing household consumption; (3) postponing new asset purchases; (4) having household members work more; (5) receiving crop insurance indemnity; (6) borrowing from financial institutions (formal loans); (7) requesting helps from relatives (informal gifts and loans); (8) receiving assistance from the government (including assistance in the forms of cash, pesticide, and seeds), and (9) receiving debt moratorium (conditional on already having debt before the flood). Activities (1) to (4) are collectively grouped as self-insurance mechanisms. Activities (5) and (6) are what Sawada (2014) refers to as market mechanisms, while activities (7) to (9) are non-market mechanisms provided by community and government.[8] Note that these activities were not mutually exclusive and some households engaged in multiple activities at the same time.

[8] Since agricultural loans were largely from the government-run Bank of Agriculture and Agricultural Cooperatives (BAAC), we classify debt moratorium as one type of government assistance in this study.

Table 3.4 presents the descriptive statistics of the activities the flooded households adopted during the 2011 mega flood. The table shows the variations in activates across provinces, although two salient mechanisms were adopted widely in all of the provinces: borrowing from financial institutions and receiving cash assistance from the government. Specifically, 71 percent of flooded households in Pitsanulok reported that they responded to the 2011 flood by borrowing money from financial institutions, while 60 percent received cash assistance from the government. The relative importance of these two activities was opposite for Khonkaen where 78 percent of flooded households received cash assistance from the government while 30 percent borrowed money from financial institutions. In the other two provinces, Suphanburi and Nakorn Ratchasima, about half of the flooded households reported that they had borrowed money from financial institutions and about half of the flooded households had received cash assistance from the government.

Table 3.4: Descriptive Statistics of Risk Coping Strategies during the 2011 Mega Flood by Province

Variable	No. Obs.	Mean	Std. Dev.	Min	Median	Max	No. Obs.	Mean	Std. Dev.	Min	Median	Max
	Suphanburi						*Pitsanulok*					
Sell assets	56	0,04	0,19	0	0	1	97	0,04	0,20	0	0	1
Reduce household consumption	56	0,13	0,33	0	0	1	97	0,29	0,46	0	0	1
Postpone new asset purchase	56	0,13	0,33	0	0	1	97	0,01	0,10	0	0	1
Have household members work more	56	0,02	0,13	0	0	1	97	0,09	0,29	0	0	1
Receive crop insurance indemnity	56	0,00	0,00	0	0	0	97	0,00	0,00	0	0	0
Borrow from financial institutions	56	0,46	0,50	0	0	1	97	0,71	0,46	0	1	1
Request helps from relatives	56	0,13	0,33	0	0	1	97	0,12	0,33	0	0	1
Receive financial assistance from government, cash	56	0,46	0,50	0	0	1	97	0,60	0,49	0	1	1
Receive financial assistance from government, pesticide	56	0,00	0,00	0	0	0	97	0,00	0,00	0	0	0
Receive financial assistance from government, seeds	56	0,05	0,23	0	0	1	97	0,05	0,22	0	0	1
Receive debt moratorium, conditional on having debt	44	0,73	0,45	0	1	1	89	0,88	0,33	0	1	1
	Khonkaen						*Nakorn Ratchasima*					
Sell assets	54	0,04	0,19	0	0	1	46	0,07	0,25	0	0	1
Reduce household consumption	54	0,13	0,34	0	0	1	46	0,15	0,36	0	0	1
Postpone new asset purchase	54	0,09	0,29	0	0	1	46	0,02	0,15	0	0	1
Have household members work more	54	0,19	0,39	0	0	1	46	0,07	0,25	0	0	1
Receive crop insurance indemnity	54	0,13	0,34	0	0	1	46	0,13	0,34	0	0	1
Borrow from financial institutions	54	0,30	0,46	0	0	1	46	0,48	0,51	0	0	1
Request helps from relatives	54	0,22	0,42	0	0	1	46	0,11	0,31	0	0	1
Receive financial assistance from government, cash	54	0,78	0,42	0	1	1	46	0,48	0,51	0	0	1
Receive financial assistance from government, pesticide	54	0,00	0,00	0	0	0	46	0,00	0,00	0	0	0
Receive financial assistance from government, seeds	54	0,02	0,14	0	0	1	46	0,00	0,00	0	0	0
Receive debt moratorium, conditional on having debt	30	0,47	0,51	0	0	1	43	0,23	0,43	0	0	1

Some other interesting findings are as follows: First, the majority of government assistance came in the form of cash. Only a small fraction of flooded households received non-cash assistance from the government (pesticide and seeds). Second, crop insurance did not exist in Suphanburi and Pitsanulok, but about 13 percent of flooded households in the northeast received insurance indemnity following the 2011 flood. This finding reflects the low take-up of crop insurance in Thailand in general. Third, the majority of households did not rely on their own self-insurance mechanisms during the 2011 flood, although reducing household consumption and having household members work more were not negligible. Finally, among the flooded households who had debt prior to the 2011 flood, most of the households in the Chao Phraya-Thachin area got debt moratorium (88 percent in Pitsanulok and 72 percent in Suphanburi), while less than half of the households in the northeast received such assistance (47 percent in Khonkaen and 23 percent in Nakorn Ratchasima). This is consistent with the fact that damage from the flood was less severe in the northeast, as shown above in Table 3.2.

3.2. Subjective Expectations

Our survey incorporated expectation questions for eliciting subjective probabilities of future flood events, flood damage, and disaster relief provided by the government. Subjective probabilities were elicited for the occurrence of flood events in the next ten years (no flood, mild floods, or severe floods similar to the 2011 mega flood).[9] Table 3.5 presents descriptive statistics of the responses from the households in our sample, stratified by their experience of the 2011 mega flood (directly hit by the flood versus not directly hit by the flood) *and* their exposure to floods (being in a flood-prone area versus not being in a flood prone area), in the 2x2 matrix.

[9] In the field, ten one-baht coins were used as visual aids to express the probabilistic concept since we were afraid that it might be too abstract to ask respondents for a probability directly. Table A in Appendix 1 was presented to a farmer on a sheet of paper, while he/she was asked to allocate ten one-baht coins into the given intervals. Each coin represents one chance out of ten. The allocation of coins thus expresses the strength of belief a particular farmer has about the likelihood of a specific event happening.

Table 3.5: Descriptive Statistics of Subjective Expectations

Variable	No. Obs.	Mean	Std. Dev.	Min	Median	Max	No. Obs.	Mean	Std. Dev.	Min	Median	Max
	Mega Flood = 0, Flood Prone = 0						*Mega Flood = 0, Flood Prone = 1*					
Prob (Mild flood)	137	0,33	0,27	0	0,3	1	36	0,54	0,25	0	0,5	1
Prob (Partial damage | Mild flood)	137	0,38	0,35	0	0,4	1	36	0,40	0,33	0	0,4	1
Prob (Total damage | Mild flood)	137	0,10	0,18	0	0	1	36	0,16	0,25	0	0	1
Prob (Government assistance | Mild flood)	137	0,33	0,34	0	0,3	1	36	0,41	0,28	0	0,5	1
Prob (Severe flood)	137	0,16	0,19	0	0,1	1	36	0,24	0,19	0	0,2	1
Prob (Partial damage | Severe flood)	137	0,22	0,28	0	0	1	36	0,16	0,24	0	0	1
Prob (Total damage | Severe flood)	137	0,47	0,42	0	0,5	1	36	0,63	0,42	0	0,8	1
Prob (Government assistance | Severe flood)	137	0,69	0,35	0	0,8	1	36	0,82	0,28	0	1	1
Household able to cope with future flood (0=no, 1=partially, 2=totally)	137	1,15	0,84	0	1	2	36	0,69	0,79	0	0,5	2
Community able to cope with future flood (0=no, 1=partially, 2=totally)	137	1,22	0,72	0	1	2	36	0,92	0,65	0	1	2
Government able to cope with future flood (0=no, 1=partially, 2=totally)	137	1,24	0,75	0	1	2	36	1,03	0,74	0	1	2
	Mega Flood = 1, Flood Prone = 0						*Mega Flood = 1, Flood Prone = 1*					
Prob (Mild flood)	150	0,47	0,24	0	0,45	1	103	0,55	0,25	0	0,5	1
Prob (Partial damage | Mild flood)	150	0,47	0,28	0	0,5	1	103	0,45	0,30	0	0,5	1
Prob (Total damage | Mild flood)	150	0,25	0,27	0	0,2	1	103	0,31	0,32	0	0,2	1
Prob (Government assistance | Mild flood)	150	0,40	0,34	0	0,5	1	103	0,39	0,35	0	0,4	1
Prob (Severe flood)	150	0,27	0,21	0	0,2	1	103	0,30	0,21	0	0,3	1
Prob (Partial damage | Severe flood)	150	0,17	0,26	0	0	1	103	0,14	0,23	0	0	1
Prob (Total damage | Severe flood)	150	0,80	0,31	0	1	1	103	0,82	0,28	0	1	1
Prob (Government assistance | Severe flood)	150	0,83	0,26	0	1	1	103	0,77	0,32	0	1	1
Household able to cope with future flood (0=no, 1=partially, 2=totally)	150	0,57	0,69	0	0	2	103	0,36	0,57	0	0	2
Community able to cope with future flood (0=no, 1=partially, 2=totally)	150	0,65	0,63	0	1	2	103	0,60	0,62	0	1	2
Government able to cope with future flood (0=no, 1=partially, 2=totally)	150	0,96	0,70	0	1	2	103	0,79	0,67	0	1	2

When the households were asked about the likelihood of no flood, mild floods, or severe floods in the next ten years, it makes intuitive sense that the households not living in flood-prone areas (left panel) had lower subjective expectations of future mild floods. The subjective expectations were higher for those located in flood-prone areas (right panel). The table also suggests that being directly hit by the 2011 mega flood increased the subjective expectation of future mild floods (top versus bottom panels). Specifically, the 2011 mega flood corresponded to the subjective expectation of future mild floods of 0.47 (much higher as compared to 0.33) for those not in flood-prone areas, and 0.55 (only slightly higher as compared with 0.54) for those located in flood-prone areas. Although the subjective expectations of future severe floods were lower for all four groups of sampled households, a similar pattern was found for the subjective expectations of future severe floods across four groups of households. In particular, households in flood-prone areas had higher subjective expectations compared with to those in non-flood prone areas, and being directly hit by the 2011 mega flood resulted in a higher subjective expectation of future severe floods for both flood-prone and non-flood-prone households.

Next, the survey elicited subjective expectations of loss, conditional on the incidence of mild floods or severe floods (no loss, partial damage, or total damage). The table shows that, conditional on the event of mild floods, households in the flood-prone areas had higher expectations of both partial and total damage from future mild floods. The 2011 mega flood, however, increased the subjective expectations of- damage for both flood prone and non-flood-prone households. A similar pattern was found for the case of damage conditional on future severe floods. The main difference was that the subjective expectations of the event of total damage from severe floods were much higher than in the case of mild floods, especially for those located in the flood-prone areas. Specifically, for those not directly hit by the 2011 flood, the subjective expectations of the event of total damage conditional on severe floods were 0.47 for non-flood-prone households and 0.63 for flood-prone households. With the 2011 flood, the probabilities increased to 0.80 and 0.82 for these two groups, respectively.

Finally, the questionnaire asked what each household thought about the ability of household, community, and government to cope with future floods. The responses were on a scale of 0 to 2 (0 = not able, 1 = partially able, and 2 = totally able). The results show that, on average, the responses were higher for households in the non-flood-prone areas than for those in the flood-prone areas. However, the 2011 mega flood reduced the subjective expectations of the ability of household, community, and government to cope with future floods for both non-flood-prone and flood-prone-households.

We further analysed statistically whether the differences in subjective expectations across households in our sample were induced by the 2011 mega flood event. Columns (1) to (8) of Table 3.6 present the results from linear probability regression analyses, using the responses discussed above as dependent variables and controlling for households' characteristics as well as district (amphoe) fixed effects.[10] Intuitively, the results show that being in flood-prone areas was positively correlated with the higher subjective probability of future floods, both for mild floods (column 1) and severe floods (column 5). However, being directly hit by the 2011 mega flood was also positively associated with higher subjective expectation of future floods, suggesting that the mega flood may have induced households' higher expectations. For both mild and severe floods, the interaction term was negative (though not statistically significant for severe floods), implying that

[10] District (or amphoe) is an administrative unit in Thailand. It is smaller than province (or changwat) but larger than county (or tambon). Our sample households came from 12 districts: two in Pitsanulok, three in Suphanburi, six in Khonkaen, and one in Nakorn Ratchasima.

the effect of the mega flood on subjective probability of future floods was smaller if the households were already in the flood–prone areas. In other words, if the households were not prone to floods before the 2011 mega flood, the mega flood had a higher impact on their subjective probability of future floods than those who were acquainted with regular floods. The table also shows that the 2011 mega flood was positively associated with higher subjective expectations of both partial and total damage from mild floods (columns 2 and 3) and total damage from severe floods (column 7). Interestingly, being directly hit by the 2011 mega flood and being in the flood-prone areas were positively correlated with the subjective expectation of government assistance in case of severe floods, but not in the event of mild floods (columns 8 and 4, respectively). Surprisingly, for future severe flood events, the interaction term was negative. This finding suggested that, for the flood-prone households, experiencing the mega flood in 2011 reduced their subjective probability of government assistance. One of the explanations could be the reduced credibility of government assistance in the presence of widespread natural disasters as compared with such assistance during normal floods, probably due to a lack of resources or mismanagement at times of such rare, severe, and nationwide events.

Table 3.6: Regression Analysis of Subjective Expectations

	(1) Prob (Mild flood)	(2) Prob (Partial damage | Mild flood)	(3) Prob (Total damage | Mild flood)	(4) Prob (Government assistance | Mild flood)	(5) Prob (Severe flood)	(6) Prob (Partial damage | Severe flood)	(7) Prob (Total damage | Severe flood)	(8) Prob (Government assistance | Severe flood)	(9) Household able to cope with future flood	(10) Community able to cope with future flood	(11) Government able to cope with future flood
Flood 2011 = 1	0.101***	0.104***	0.147***	0.0694	0.0870***	-0.0589	0.342***	0.160***	-0.510***	-0.499***	-0.134
	(0.0324)	(0.0397)	(0.0307)	(0.0440)	(0.0266)	(0.0359)	(0.0476)	(0.0416)	(0.0974)	(0.0862)	(0.0947)
Flood prone = 1	0.169***	0.0108	0.0701	0.0983*	0.0761**	-0.0627	0.165**	0.144**	-0.348**	-0.212*	-0.0964
	(0.0472)	(0.0616)	(0.0460)	(0.0564)	(0.0368)	(0.0473)	(0.0799)	(0.0569)	(0.144)	(0.125)	(0.136)
Flood 2011 x Flood prone	-0.113**	-0.0435	-0.00253	-0.0902	-0.0425	0.0250	-0.136	-0.206***	0.140	0.180	-0.0288
	(0.0559)	(0.0720)	(0.0590)	(0.0702)	(0.0455)	(0.0565)	(0.0876)	(0.0675)	(0.162)	(0.146)	(0.159)
Household size	-0.00904	0.0123	0.00593	0.00456	0.00964	0.00931	0.00615	-0.00228	0.0384*	0.0323*	-0.0155
	(0.00725)	(0.00825)	(0.00759)	(0.00944)	(0.00605)	(0.00743)	(0.00981)	(0.00764)	(0.0200)	(0.0180)	(0.0204)
Household assets	0.0239*	0.00600	-0.0150	-0.0416**	-0.00743	0.00131	0.0117	-0.00787	0.0245	-0.0222	-0.0551
	(0.0130)	(0.0165)	(0.0129)	(0.0168)	(0.0115)	(0.0152)	(0.0187)	(0.0148)	(0.0366)	(0.0324)	(0.0337)
Household head = Male	-0.0243	-0.00409	-0.0204	0.0219	0.0279	-0.0387	0.0347	-0.0196	0.0791	0.0608	0.0786
	(0.0267)	(0.0335)	(0.0279)	(0.0360)	(0.0200)	(0.0292)	(0.0388)	(0.0308)	(0.0731)	(0.0661)	(0.0705)
Household's age	0.000277	-0.00159	0.000521	-0.00284	-0.0000227	0.00142	-0.00209	-0.00350**	0.00246	-0.000772	-0.00920**
	(0.00126)	(0.00164)	(0.00148)	(0.00174)	(0.00108)	(0.00133)	(0.00182)	(0.00163)	(0.00366)	(0.00355)	(0.00360)
Household head's eduation = Primary	-0.00286	-0.0118	-0.0124	0.00756	0.0109	-0.00874	0.0300	0.0730**	-0.117	0.0201	-0.0443
	(0.0345)	(0.0380)	(0.0350)	(0.0428)	(0.0271)	(0.0371)	(0.0460)	(0.0368)	(0.0948)	(0.0822)	(0.0911)
Constant	0.0903	0.344	0.267	0.982***	0.203	0.122	0.348	0.935***	0.523	1.307***	2.405***
	(0.180)	(0.247)	(0.181)	(0.241)	(0.171)	(0.206)	(0.273)	(0.219)	(0.531)	(0.491)	(0.497)
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	426	426	426	426	426	426	426	426	426	426	426

The last three columns of the table analyse the subjective expectations of household's, community's, and government's ability to cope with future flood events. The regression results show that experiencing the 2011 mega flood and being in flood-prone areas were negatively associated with expectations of the household's and community's ability (columns 9 and 10) to cope with future floods, but were not statistically correlated with expectations of the government's ability to cope with future floods (column 11).

3.3. Preferences

The survey asked hypothetical questions that allow us to elicit preferences of the farming households in our sample. Table 3.7 presents descriptive statistics of four simple measures that capture risk, time, and social preferences: (1) risk aversion, (2) loss aversion, (3) impatience, and (4) altruism.[11] Again, the sampled households were stratified according to whether the household was in a flood-prone area and whether the household directly experienced the 2011 mega flood.

Table 3.7: Descriptive Statistics of Household's Preference Measures

Variable	No. Obs.	Mean	Std. Dev.	Min	Median	Max	No. Obs.	Mean	Std. Dev.	Min	Median	Max
	Mega Flood = 0, Flood Prone = 0						*Mega Flood = 0, Flood Prone = 1*					
Risk aversion (1=min, 5=max)	120	3,99	1,15	1	4	5	32	3,63	1,45	1	4	5
Loss aversion (1=min, 5=max)	128	4,65	0,84	1	5	5	36	4,11	1,39	1	5	5
Impatience (1=min, 3=max)	137	2,18	0,79	1	2	3	36	2,31	0,79	1	2,5	3
Altruism (0=min, 1=max)	137	0,28	0,24	0	0,5	0,5	36	0,27	0,25	0	0,5	0,5
	Mega Flood = 1, Flood Prone = 0						*Mega Flood = 1, Flood Prone = 1*					
Risk aversion (1=min, 5=max)	130	4,20	0,99	1	4,5	5	92	3,92	1,19	1	4	5
Loss aversion (1=min, 5=max)	143	4,51	0,98	1	5	5	97	4,41	1,07	1	5	5
Impatience (1=min, 3=max)	150	2,24	0,77	1	2	3	103	2,27	0,72	1	2	3
Altruism (0=min, 1=max)	150	0,23	0,24	0	0,05	0,5	103	0,27	0,24	0	0,5	0,5

The table shows that our sample households were relatively risk averse. On the scale of 1 (least averse) to 5 (most averse), both the mean and the median measures of risk aversion were around 4 in all four groups. However, the findings suggest that households in flood-prone areas were slightly less risk averse than those in non-flood-prone areas.[12] The 2011 mega flood seemed to

[11] See Appendix 2 for the hypothetical questions.
[12] On the one hand, this finding may seem to reflect the endogenous choices of farmland of the households. On the other hand, rice farms in Thailand are usually inherited so location choices are typically determined by previous generations.

be associated with higher risk aversion for both flood-prone and non-flood-prone households. The results were more mixed for our measure of loss aversion. Regarding time preference, the four groups showed a similar mean and median for impatience, at around 2, on a scale from 1 (least impatient) to 3 (most impatient).[13] Finally, regarding altruism, households were asked to play a dictator game. On a scale of 0 (least altruistic) to 1 (most altruistic), the top panel shows that both flood-prone and non-flood-prone households had about the same average altruism measure—approximately 0.26. However, the mega flood seemed to affect non-flood prone and flood prone households differently. For non-flood-prone households, the average altruism measure dropped to 0.23, while the measure remained similar, at 0.27, for the flood-prone group.

Finally, Table 3.8 presents regression results when we control for household characteristics and district-fixed effects. The table shows that the 2011 mega flood was positively associated with higher risk aversion. This result is consistent with the finding in Cassar, *et al.* (2011), who found a similar result in their study of the 2004 Indian Ocean tsunami in Thailand. However, our study shows that the 2011 mega flood was associated with lower altruism, opposite to what Cassar, Healy and Kesseler found. Our finding shows that the 2011 mega flood made households become less altruistic, probably because they realised the limitation of risk sharing in the presence of aggregate shocks. Finally, our findings show that the 2011 mega flood was not statistically correlated with our measures of loss aversion and time preference.

[13] Note that our simple measure of time preference is subject to risk aversion, as preferring to accept lower instantaneous payment rather than waiting for higher future payment may reflect risk aversion to future payment in addition to time impatience.

Table 3.8: Regression Analysis of Preference Measures

	(1) Risk aversion	(2) Risk aversion	(3) Loss aversion	(4) Loss aversion	(5) Impatience	(6) Impatience	(7) Altruism	(8) Altruism
Flood 2011 = 1	0.302*	0.294*	-0.144	-0.108	0.0618	0.0911	-0.0659**	-0.0665**
	(0.155)	(0.152)	(0.128)	(0.126)	(0.0992)	(0.102)	(0.0314)	(0.0317)
Flood prone = 1	-0.346	-0.322	-0.501**	-0.523**	0.123	0.130	-0.0250	-0.0320
	(0.284)	(0.279)	(0.239)	(0.241)	(0.152)	(0.150)	(0.0466)	(0.0462)
Flood 2011 x Flood prone	0.0694	0.0544	0.468*	0.503*	-0.102	-0.0983	0.0759	0.0770
	(0.321)	(0.316)	(0.270)	(0.272)	(0.178)	(0.177)	(0.0557)	(0.0555)
Household size		0.0152		-0.0348		-0.0336		0.00172
		(0.0338)		(0.0267)		(0.0211)		(0.00707)
Household assets		-0.0665		-0.0118		-0.0259		0.0150
		(0.0617)		(0.0455)		(0.0406)		(0.0125)
Household head = Male		0.143		-0.234***		0.0155		-0.0458*
		(0.137)		(0.0892)		(0.0832)		(0.0260)
Household's age		0.00170		0.000110		-0.000956		-0.00123
		(0.00632)		(0.00544)		(0.00412)		(0.00127)
Household head's eduation = Primary		-0.123		0.0356		0.0694		0.0331
		(0.151)		(0.132)		(0.102)		(0.0321)
Constant	3.935***	4.650***	4.633***	5.033***	2.180***	2.625***	0.288***	0.158
	(0.114)	(0.910)	(0.0880)	(0.738)	(0.0717)	(0.593)	(0.0222)	(0.184)
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	374	374	404	404	426	426	426	426

Note: Robust standard errors in parentheses. * represents p<0.10, ** p<0.05, and p<0.01

3.4. Strategies for Future Floods

Given it had been over two years since the 2011 mega flood took place, our survey took advantage of this and asked each household whether they were adopting strategies that would help mitigate the severity and damage of future flood events. The strategies we asked about include: (1) accumulating assets, (2) increasing savings, (3) having household members take on additional work outside the agricultural sector, (4) diversifying crops, (5) reducing rice growing area, (6) adjusting the mode of rice growing, (7) adjusting the method of rice growing,[14] (8) digging a pond in their rice farm, (9) building a flood prevention system themselves, and (10) building a flood prevention system with the community, and (11) insuring against crop damage. Note that strategies (1) and (2) are households building their own buffer stocks. Strategies (3) to (5) are various ways of income diversification. Strategies (6) and (7) are changes in production technology. Strategies (8) to (10) are preventive measures. Finally, strategy (11) is a market-based insurance.

[14] Changes in the mode of rice growing include changing rice varieties, changing growing/harvesting time, or avoiding growing rice during particular periods. Changes in the method of rice growing include using more chemical or more organic fertilizers and pesticides.

The top panel of Table 3.9 shows that 33 percent of flood-prone households were adopting at least one of the strategies that would mitigate the severity of future floods (top right panel), while only 21 percent of the non-flood-prone households had adopted such strategies (top left panel). Compared with the top panel, the bottom panel of Table 9 presents a striking result that households directly hit by the 2011 mega flood had adopted at least one of the strategies listed above—47 percent for the non-flood prone households (bottom left panel) and 59 percent for the flood-prone households (bottom right panel). The most commonly adopted strategies were building a flood prevention system (either by the households themselves or with the community) and adjusting the mode of rice growing. Farming households also became more diversified and more likely to purchase crop insurance after being hit by the mega flood.

Table 3.9: Descriptive Statistics of Strategies for Future Floods

Variable	No. Obs.	Mean	Std. Dev.	Min	Median	Max	No. Obs.	Mean	Std. Dev.	Min	Median	Max
	Mega Flood = 0, Flood Prone = 0						*Mega Flood = 0, Flood Prone = 1*					
Have household members work additionally outside agricultural sector	137	0,04	0,21	0	0	1	36	0,06	0,23	0	0	1
Insure crops	137	0,01	0,09	0	0	1	36	0,03	0,17	0	0	1
Increase savings (deposits)	137	0,06	0,24	0	0	1	36	0,08	0,28	0	0	1
Accumulate assets	137	0,02	0,15	0	0	1	36	0,00	0,00	0	0	0
Diversify crops	137	0,03	0,17	0	0	1	36	0,03	0,17	0	0	1
Reduce rice growing area	137	0,02	0,15	0	0	1	36	0,00	0,00	0	0	0
Adjust mode of rice growing	137	0,07	0,25	0	0	1	36	0,08	0,28	0	0	1
Adjust method of rice growing	137	0,07	0,25	0	0	1	36	0,03	0,17	0	0	1
Dig pond in rice farm	137	0,01	0,12	0	0	1	36	0,06	0,23	0	0	1
Build flood prevention system by itself	137	0,07	0,25	0	0	1	36	0,11	0,32	0	0	1
Build flood prevention system with community	137	0,05	0,22	0	0	1	36	0,03	0,17	0	0	1
Have at least one future strategy = 1	137	0,21	0,41	0	0	1	36	0,33	0,48	0	0	1
	Mega Flood = 1, Flood Prone = 0						*Mega Flood = 1, Flood Prone = 1*					
Have household members work additionally outside agricultural sector	150	0,12	0,33	0	0	1	103	0,13	0,33	0	0	1
Insure crops	150	0,09	0,28	0	0	1	103	0,08	0,27	0	0	1
Increase savings (deposits)	150	0,13	0,34	0	0	1	103	0,09	0,28	0	0	1
Accumulate assets	150	0,02	0,14	0	0	1	103	0,02	0,14	0	0	1
Diversify crops	150	0,07	0,25	0	0	1	103	0,07	0,25	0	0	1
Reduce rice growing area	150	0,01	0,08	0	0	1	103	0,03	0,17	0	0	1
Adjust mode of rice growing	150	0,19	0,39	0	0	1	103	0,24	0,43	0	0	1
Adjust method of rice growing	150	0,05	0,23	0	0	1	103	0,10	0,30	0	0	1
Dig pond in rice farm	150	0,03	0,16	0	0	1	103	0,09	0,28	0	0	1
Build flood prevention system by itself	150	0,17	0,37	0	0	1	103	0,30	0,46	0	0	1
Build flood prevention system with community	150	0,23	0,42	0	0	1	103	0,20	0,40	0	0	1
Have at least one future strategy = 1	150	0,47	0,50	0	0	1	103	0,59	0,49	0	1	1

Table 3.10 presents the results from linear probability regression analyses when we control for household characteristics and district-fixed effects. The table shows that households that were directly hit by the 2011 mega flood tended to adopt at least one of the strategies that would help mitigate the severity or the damage of future floods. The table also shows that the more risk averse the households, the higher the tendency to adopt such strategies. Finally, the results from the table show that the higher probability of government assistance in the case of damage from either mild or severe floods was not statistically correlated with the adoption of such strategies, suggesting that there was no crowding out

effect of government assistance on private strategies toward future floods. In other words, there seemed to be no moral hazard problem arising from the government implicit insurance through disaster assistance. This finding is consistent with the discussion of Table 3.5 above, showing that households perceived that the government's ability to cope with future floods was in fact quite low.

Table 3.10: Regression Analysis of Strategies for Future Floods

	(1) future_strategy	(2) future_strategy	(3) future_strategy	(4) future_strategy
Flood 2011 = 1	0.213***	0.178***	0.179***	0.184***
	(0.0538)	(0.0628)	(0.0638)	(0.0642)
Flood prone = 1	0.0891	0.125	0.126	0.121
	(0.0845)	(0.0914)	(0.0929)	(0.0958)
Flood 2011 x Flood prone	0.0132	0.00664	0.00419	0.0139
	(0.102)	(0.110)	(0.112)	(0.114)
Risk aversion		0.0341*	0.0344*	0.0386**
		(0.0191)	(0.0191)	(0.0196)
Loss aversion		-0.0198	-0.0197	-0.0230
		(0.0252)	(0.0254)	(0.0260)
Impatience		-0.0194	-0.0203	-0.0211
		(0.0302)	(0.0299)	(0.0304)
Altruism		0.0293	0.0346	0.0193
		(0.0968)	(0.0965)	(0.0983)
Prob (Government Assistance | Mild Flood)			-0.0723	-0.0557
			(0.0717)	(0.0737)
Prob (Government Assistance | Severe Flood)			0.0252	0.0189
			(0.0786)	(0.0804)
Household size				-0.0171
				(0.0124)
Household rice revenue (%)				0.000115
				(0.000843)
Household assets				0.0297
				(0.0240)
Household head = Male				-0.0484
				(0.0515)
Household head's age				0.00104
				(0.00229)
Household head's education = Primary				0.0266
				(0.0612)
Constant	0.247***	0.265	0.271	-0.0981
	(0.0374)	(0.162)	(0.167)	(0.397)
District fixed effects	Yes	Yes	Yes	Yes
Number of observations	426	355	355	353

Note : Robust standard errors in parentheses. * represents p<0.10, ** p<0.05, and p<0.01.

4. Policy Implications

The empirical findings discussed in the previous sections show that being directly hit by the 2011 mega flood did affect some household's subjective expectations, preferences, and behaviours. Firstly, the flood seemed to make the Thai farming households adjust upward their subjective expectations of future flood events, for both mild and severe floods. The flooded households also had higher expectations of possible damage caused by future floods. For households located in the non-flood prone areas, the 2011 mega flood led to higher subjective expectations of government assistance in case of severe floods, but not in the event of mild floods. However, for flood-prone households, experiencing the mega flood in 2011 actually reduced their subjective expectation of government assistance. Related, we also find that there was no crowding out effect of government assistance on private strategies for the management future flood risk and there seemed to be no moral hazard problem arising from the government implicit insurance through disaster assistance. These findings shed light on the credibility of government assistance in the event of widespread natural disasters as compared with such assistance during normal floods received by these households in the past. Lack of resources or mismanagement at times of such rare and severe nationwide events could be an explanation for this decrease in subjective expectations. The Yingluck government had proposed a comprehensive plan of water management for the whole country, and a similar plan was declared a national agenda and committed to by the National Council for Peace and Order (NCPO) following the 2014 coup d'état. If eventually implemented, the plan may help ensure a more effective government role in preventing or mitigating future floods.

Secondly, the 2011 mega flood was positively associated with higher risk aversion. This finding is consistent with the findings that the flood caused households to adopt strategies to mitigate the severity and the damage of future floods and that more risk averse households were more likely to adopt such strategies. Given that most households have already tended to insure themselves through various mechanisms, the government could supplement their initiatives by providing technical assistance regarding switching to rice varieties that are more resistant to flood water, adjusting modes of rice production based on seasonal weather forecasts, or constructing flood prevention infrastructures. The government could also facilitate households' access to nonagricultural occupations, thus providing them with opportunities to diversify their incomes.

Finally, the mega flood was negatively correlated with our measure of altruism. The households that were directly hit by the flood seemed to be less altruistic. Although possible explanations are mere speculation, the mega flood may have made them realise the limitations of risk sharing in the event of aggregate shocks. Under such circumstances, the government, especially through the Bank of Agriculture and Agricultural Cooperatives (BAAC), may encourage farming households to purchase crop insurance contracts that would help them insure their outputs beyond their local informal insurance.

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Appendix 1: Survey Questionnaire for Subjective Expectation

Table A: The elicitation of subjective expectations

<table>
<tr><td colspan="7">Question: The likelihood that the following flood events will occur in the next 10 years</td></tr>
<tr><td>No flood
</td><td colspan="3">Mild flood [F_2]
</td><td colspan="3">Severe flood [F_3]
</td></tr>
<tr><td>$P(\mathrm{F}_1)$
(coins)</td><td colspan="3">$P(\mathrm{F2}\ \ )$
(coins)</td><td colspan="3">$P(\mathrm{F}_3)$
(coins)</td></tr>
<tr><td rowspan="6"></td><td colspan="3">Q2: The likelihood that the occurrence of mild flood will affect rice production</td><td colspan="3">Q3: The likelihood that the occurrence of severe flood will affect rice production</td></tr>
<tr><td>No damage</td><td>Partial damage</td><td>Total damage</td><td>No damage</td><td>Partial damage</td><td>Total damage</td></tr>
<tr><td>$P(\mathrm{D}_1|\mathrm{F}_2)$
(coins)</td><td>$P(\mathrm{D}_2|\mathrm{F}_2)$
(coins)</td><td>$P(\mathrm{D}_3|\mathrm{F}_2)$
(coins)</td><td>$P(\mathrm{D}_1|\mathrm{F}_3)$
(coins)</td><td>$P(\mathrm{D}_2|\mathrm{F}_3)$
(coins)</td><td>$P(\mathrm{D}_3|\mathrm{F}_3)$
(coins)</td></tr>
<tr><td rowspan="3"></td><td colspan="2">Q4: The likelihood that farmer will receive relief when mild flood occurs</td><td rowspan="3"></td><td colspan="2">Q5: The likelihood that farmer will receive relief when severe flood occurs</td></tr>
<tr><td>Yes</td><td>No</td><td>Yes</td><td>No</td></tr>
<tr><td>$P(\mathrm{Yes}|\mathrm{F}_2)$
(coins)</td><td>$P(\mathrm{No}|\mathrm{F}_2)$
(coins)</td><td>$P(\mathrm{Yes}|\mathrm{F}_3)$
(coins)</td><td>$P(\mathrm{No}|\mathrm{F}_3)$
(coins)</td></tr>
</table>

Appendix 2: Survey Questionnaires for Risk, Time, and Social Preferences

A.2.1 Risk Aversion

Suppose there are seven rice varieties and each variety gives a different yield. Some varieties give a low yield but are resistant to disease, pests, and natural disasters. Some varieties give a higher yield but are not resistant to disease, pests, and natural disasters, and give very low yields when disease, pests, or natural disasters occur. If you did not know whether such disasters would happen next year, but you knew that the chances that such disasters would or would not happen are even, which variety of rice would you choose to grow?

Rice Variety	Yield (Output per Rai) in the year that disease, pests, or natural disasters occurred	Yield (Output per Rai) in the year that disease, pests, or natural disasters did not occur
1	700	700
2	630	1,330
3	560	1,680
4	420	2,100
5	280	2,240
6	140	2,660
7	0	2,800

A.2.2 Loss Aversion

Suppose you had to choose between two choices. If you opted for choice A, you would certainly lose money. But if you opted for choice B, there would be a coin toss—you would lose 2,000 baht in case of head but you would lose nothing in case of tail. Which choice would you pick in each of these scenarios?

Scenario	Choice A	Choice B	Your Choice
1	Lose 1,200 baht	Lose 2,000 baht if head Lose nothing if tail	
2	Lose 1,000 baht	Lose 2,000 baht if head Lose nothing if tail	
3	Lose 700 baht	Lose 2,000 baht if head Lose nothing if tail	
4	Lose 500 baht	Lose 2,000 baht if head Lose nothing if tail	
5	Lose 200 baht	Lose 2,000 baht if head Lose nothing if tail	

A.2.3 Time Preference

Suppose you had to choose between two choices. If you opted for choice A, you would receive 1,000 baht in cash tomorrow. But if you opted for choice B, you would receive more than 1,000 baht in cash in 2 weeks and 1 day (15 days). In each scenario, which choice would you select?

Scenario	Choice A	Choice B	Your Choice
1	Receive 1,000 baht tomorrow	Receive 1,000 baht in 15 days	
2	Receive 1,000 baht tomorrow	Receive 1,010 baht in 15 days	
3	Receive 1,000 baht tomorrow	Receive 1,020 baht in 15 days	
4	Receive 1,000 baht tomorrow	Receive 1,050 baht in 15 days	
5	Receive 1,000 baht tomorrow	Receive 1,100 baht in 15 days	
6	Receive 1,000 baht tomorrow	Receive 1,400 baht in 15 days	
7	Receive 1,000 baht tomorrow	Receive 1,700 baht in 15 days	
8	Receive 1,000 baht tomorrow	Receive 2,000 baht in 15 days	

A.2.4 Altruism

Suppose we gave you 1,000 baht in cash today and matched you with another farmer from your village, but you did not know who the other farmer was and the other farmer did not know who you were. If we gave you a chance to give the other farmer a part or a total of the 1,000 baht while keeping your decision confidential, would you give the other farmer any money? And if so, how much?

CHAPTER 4
The Effects of Natural Disasters on Households' Preferences and Behaviours: Evidence from Cambodian Rice Farmers After the 2011 Mega Flood

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This paper studies the impacts of the 2011 mega flood on preferences, subjective expectations, and behavioural choices among Cambodian rice-farming households. We found flood victims to have larger risk aversion and altruism, and lower impatience and trust of friends and local governments. The disaster also induced flooded households to adjust upward their subjective expectations of future floods and of natural resources as a safety net. Mediating (partially if not all) through these changes in preferences and expectations, the 2011 flood also affected households' behavioural choices, some of which could further determine long-term economic development and resilience to future floods. We found flooded households to have lower productive investment, to substitute away social insurance with by increasing

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self-insurance and demand for market-based instruments, and more importantly, to increase the use of natural resources as insurance. These findings shed light on the design of incentive-compatible safety nets and development interventions.

1. Introduction

Natural disasters often create adverse impacts on the livelihoods of people, especially those living in developing economies where access to safety nets is limited. Disasters not only destroy physical, human, and social capital of households, catastrophic disasters can lead to a change in risk, time, and social preferences.[1] In addition, largely unexpected and rare disasters as well as the success or failure of safety net institutions in coping with disasters may lead to a revision of subjective expectations of future events. Such impacts could induce changes in behavioural choices that could in turn affect long-term economic development and resilience to future floods. Understanding these consequences also has crucial policy implications for the design of incentive-compatible safety nets and development programmes for agricultural households in rural economies.

This paper aims to make a contribution to the growing literature on the impacts of catastrophic events (natural disasters or civil conflicts) on household preferences and behaviours by studying the consequences of the 2011 mega flood in Cambodia—the country's biggest flood in recent history—on preferences, subjective expectations, and behavioural choices of affected Cambodian rice-farming households. We use the 2011 mega flood as a natural experiment and utilise discontinuity generated by this flood to create variations in flood exposure across sampled villages and households. Field surveys and experiments were used to elicit key preferences, expectations and behavioural choices.

The Cambodian 2011 mega flood was a unique natural disaster event. Although flood is the most common natural disaster in Southeast Asia, most floods occur

[1] Recent studies provide empirical evidence that natural disasters can cause changes in risk, time, and social preferences. For risk preference, see Eckel, *et al.* (2009); Cameron and Shah (2012); Cassar, *et al.* (2011); and Page, *et al.* (2012). For time preference, see Callen (2011). For social preference, see Castillo and Carter (2011); and Cassar, *et al.* (2011).

in Indonesia, the Philippines, and Thailand, while Cambodia has experienced relatively less frequent floods—only 15 occurrences during 1981-2010. However, unlike other countries in Southeast Asian, the death toll per flood event in Cambodia is the highest in the region, averaging nearly 90 casualties, i.e., a death toll nearly twice as high as in Indonesia and Thailand on a per-event basis.[2] The 2011 flood was particularly important since it was the largest and deadliest in recent decades, with a death toll nearly three times as high as the historical average. Heavy rain and overflow of the Mekong River and the Tonle Sap from the second week of August 2011 affected 18 out of 24 provinces in Cambodia. Impacts were especially severe among the rice farming communities, who tend to be poorer and more flood-prone. The flood caused 250 deaths, and more than 1.7 million people affected. More than 400,000 hectares (ha) of rice crops were affected, of which almost 230,000 ha (9.3 percent of the cultivated area) were severely damaged or destroyed. Moreover, 1,675 livestock were lost, and more than 70,000 drinking water wells were contaminated. It was estimated that the floods caused USD 625 million worth of losses and damage, with infrastructure damage estimated at USD 376 million. The damage included roads (national, provincial, and rural), irrigation facilities, water supply and sanitation facilities, schools, and health centres. The flooding posed a serious challenge to development and the livelihoods of people, particularly the poor and socially disadvantaged such as women and children.

Given its rarity and severity, the 2011 mega flood serves as an ideal natural experiment for a study of how a disaster affects households' preferences and behaviours. This study focuses particularly on the effects of the flood on rice-farming households because most of the areas directly affected by the flood in Cambodia were farmland, especially for rice cultivation, and these farms were operated by relatively poor households whose access to risk management and risk coping mechanisms was relatively limited. The mega flood therefore had substantial impacts on the livelihoods of many farming households and thus understanding these impacts would provide important insights for policymaking regarding safety nets of poor and vulnerable households.

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[2] These statistics are based on the Emergency Events Database (EM-DAT), one of the most comprehensive databases on disasters, maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Louvain (Belgium). See Samphantharak (2014) for more details.

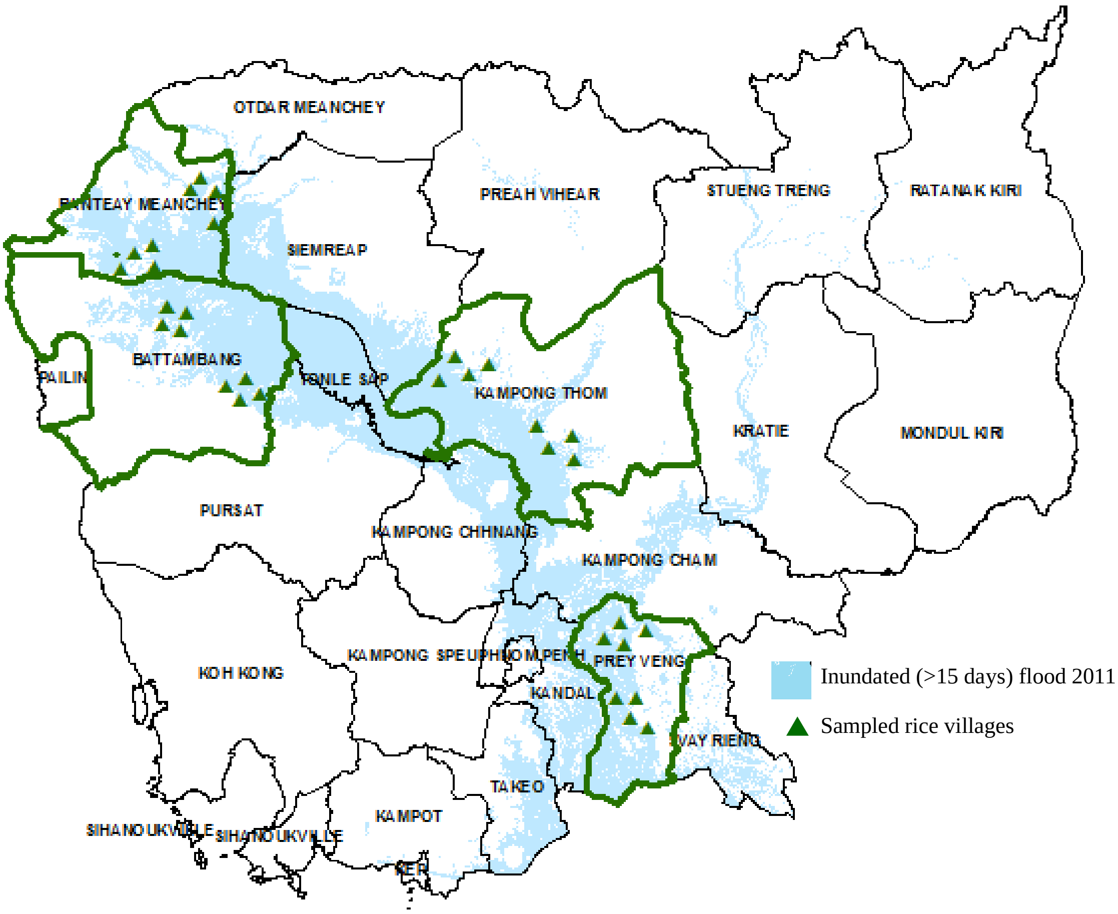
We found that the mega flood seemed to have made the affected Cambodian rice-farming households become more risk averse, and this increase in risk aversion appears greatest among poorer households. The mega flood also reduced impatience and increased altruistic behaviour among the affected households. Surprisingly, the 2011 flood, caused a significant reduction in trust of neighbours and local governments. Flood victims revised upward their subjective expectations of future severe floods and of the benefits of natural resources as a safety net. Mediating (partially if not all) through these changes in preferences and expectations, the 2011 flood also affected households' behavioural choices. We found the flooded households to have lower productive investment, to substitute away social insurance with an increase in self-insurance and demand for market-based instruments, and more importantly, to increase the use of natural resources as insurance. These findings shed light on the design of incentive-compatible safety nets and development interventions.

The paper is organised as follows. Section 2 describes our sampling strategy, our flood exposure variables, and the survey and summary statistics of our sampled households and villages. Section 3 discusses the empirical strategy we employed to identify causal impacts of the 2011 mega flood. Section 4 reports our empirical results. Section 5 concludes the paper with policy implications.

2. Data

The data used in this study are from our survey conducted in April 2014 in four of Cambodia's key rice-growing provinces: Prey Veng, Kampong Thom, Banteay Meanchey and Battambang. As shown in Figure 4.1, these four provinces were severely affected by the 2011 flood. The four provinces also represent variations in geographical settings, rice cultivation and agricultural production systems, access to market opportunities, and the extent to which household livelihoods are prone to floods. These variations could potentially contribute to the variations in the nature of the 2011 flood experience, as well as the capacity and strategies of households and communities in coping with and managing floods.

Figure 4.1: Map of studied villages



2.1. Sampling strategy

The survey and experiments cover 256 rice-farming households in 32 rice-growing villages in 16 communes in the four provinces. Four considerations underlie our sampling strategy: First, we confine our study to rice growing areas and households. Second, we utilise the discontinuity generated by the 2011 flood to construct a variation in flood experience. This discontinuity allows us to compare villages and farmers directly hit by the flood with those who did not directly experience the flood. Third, spillover and general-equilibrium effects on the non-flood households were unavoidable. These effects include, but are not limited to, new information about the flood and the management of the flood by the government as perceived by the farmers. There were also disruptions to local, regional, and national economic activities that affected prices of goods and services, as well as incomes of many households in the non-flood areas. With household-level flood experience, the effects, however, should bias our results toward finding no difference in preferences and behaviours between the farmers who were directly hit by the flood and those whose farms were not flooded. We also attempted to produce another set of comparable results to capture within-village spillover effects by creating variations in village-level 2011 flood experience.[3]

Finally, since households in the flood-prone areas could have higher chance of being affected by the 2011 mega flood, relative to those in the non-flood-prone areas and the two groups could also have different characteristics, which could potentially result in different behavioural outcomes, simply selecting and comparing outcome variables between the flood affected and unaffected villages or households could leave us with a risk of selection problem–leading our estimates to capture impacts of the flood risk rather than of the mega 2011 flood itself. Our sampling strategy, therefore, also involves further stratification by the degree to which households or villages are prone to floods to account for variations in flood risk, so that we can control for this problem outright in our econometric estimations. Overall, our sampling strategy for each province involves two stratifications, at both the village and household levels: (i) whether the village/household was flooded in 2011, and (ii) whether the village/household is generally prone to floods in normal years.

To implement our sampling strategy, we went through the following steps. First, we used official statistics of rice production by commune and village from the Cambodian Council of Agricultural and Rural Development to identify our sampling frames in each province, i.e., the rice-producing communes and villages. We then used remote sensing maps of inundated areas produced by the World Food Program (WFP) to identify (i) communes severely affected by the 2011 mega flood (i.e., areas identified as inundated for more than 15 days) and (ii) communes that are prone to floods (based on 10 years of inundation data) in our four provinces.[4] For each province, we then selected

[3] We note that our strategy thus will not capture the likely spillover effects within the flooded commune, district or even province. But with village-level flood experience, the commune-level spillovers should bias our results toward finding no effect.

[4] The WFP flood maps were based on the near real time remote sensing NASA-MODIS product with 1-km resolution. The MODIS inundation maps have been available every 15 days since 2000. Mapping of severely affected areas was done by defining severely affected areas as those (non-permanent water) areas covered with floodwater for more than 15 days (i.e., where we saw water in at least two consecutive inundation maps). The WFP's flood risk mapping utilises 10 years of inundation flood maps and produces three flood priority classifications based on the 10-year flood frequency. The first, second and third priority flood zones consist of areas that experienced at least three, two or one extended flood(s) in

four rice-growing communes with extended areas severely affected by the 2011 flood, and two of which are flood-prone. In total, 16 flooded communes were selected, half of which are flood-prone.

Within each commune, there could also be a variation in the flood experience across rice-growing villages, e.g., with respect to the share of areas/households affected. In the second step, we exploited this potential variation by defining flooded villages as villages with a majority of areas severely flooded (i.e., with large areas identified as inundated for more than 15 days). Using GIS village locators and the flood maps, we then selected two rice-growing villages—one severely flooded and another not (severely) flooded in each commune.[5] Chiefs of the chosen communes were consulted to confirm our GIS-based classification and accessibility of the chosen villages. In cases where our chosen villages did not fit our categorisation,[6] we relied on commune chiefs and commune-level data for village selection instead. In particular, a rice-growing village is classified as a flooded village if more than 50 percent of households reported rice production loss following the 2011 flood. In total, 32 rice-growing villages were selected. In sum, the sampling strategy up to this point thus allowed us to ensure the variation in village-level 2011 flood experience (severely flooded versus not [severely] flooded), as well as the variation of flood risk (flood-prone versus not flood-prone) within the flooded and non-flooded village groups.

Within each village, there could also be sources of exogenous variations of the 2011 flood experience across households. Since our sampled households were rice farmers, the variation in the 2011 flood experience could relate closely to the extent that the flood affected rice production—the variation of which then depended largely on the (largely exogenous) correlations between rice production cycle, timing of the flood, and flood severity (flood height and the

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the past ten years. We selected our flood-prone communes from the group of communes in the WFP's first flood priority.

[5] Since the 2011 mega flood was largely covariate, it was not possible to find a completely non-flooded village. Our distinction of the flooded and non-flooded villages is thus the intensity of the 2011 flood extent, observed through share of areas/households affected by flood. Our village level flood impact analysis thus explores marginal variations in the village flood experience.

[6] One of the key reasons is that the resolution of our flood maps could only allow accurate flood identification at commune level.

inundation period).[7] In the third step, we again exploited these potential variations by proceeding to generate variations in the 2011 flood experience at the household level. A household was classified as a flooded household if it reported that its rice fields were submerged by floodwater for longer than 15 days in 2011.[8] In consultation with the village chiefs during subsequent field visits, we finally selected eight rice-growing households in each village applying the following criteria: (i) both flooded (rice fields were flooded) and non-flooded (rice fields were not flooded) households were selected for each village and (ii) the rice fields of the chosen households were geographically dispersed and varied in terms of the size of farm land.

The sample size by province is shown in Panel A of Table 4.1. Note that, although we had originally intended to collect a balanced sample for flooded and non-flooded households, the sample size was largely unbalanced. The flooded households largely outnumbered non-flooded households for Kampong Thom, Banteay Meanchey and Battambang, where the majority of rice farms were flooded in 2011. Our samples were relatively more balanced in Prey Veng (29 flooded households out of 64 households).

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[7] It is possible that some of these factors could be correlated with household characteristics. For example, some advanced households may study and adjust their rice growing patterns to escape common floods. However, we argued that the majority of these factors were largely exogenous for Cambodian rice farmers. First, a large variation in the rice growing cycle was driven by variation in rice varieties. For example, long-life vs. short-life rice, or flooded vs. non-flooded rice are all common varieties in our studied areas. Second, while some farmers could learn to adjust their growing patterns to be more resilient to climate change, the extent and severity of the 2011 mega flood had been largely unexpected by rice farmers, as discussed in Section 1. In the survey, we also asked farmers if they had done anything to prepare for the 2011 flood; most answered that they had done nothing to prepare.

[8] Using this definition, our estimation results using household-flood experience should capture flood impacts on households that had seen their rice production hit directly by the 2011 flood. A common occurrence were households that did not experience rice production damage even though housing and (bare) agricultural land were flooded, e.g., if they had harvested their rice prior to the flood. Such households we classified as non-flooded households.

Table 4.1: Sampling and Summary Statistics of the 2011 Mega Flood by Studied Province

	All		Prey Veng		Kampong Thom		Banteay Meanchey		Battambang	
A. Sampled households										
Total villages	32		8		8		8		8	
Flooded villages	16		4		4		4		4	
Total households	256		64		64		64		64	
Flooded	182		29		53		46		44	
	All		Prey Veng		Kampong Thom		Banteay Meanchey		Battambang	
B. Characteristics of flood 2011	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Starting month	8.97	0.86	8.79	0.95	8.87	0.92	8.99	0.93	9.22	0.55
Flood height	3.09	0.92	1.98	1.00	3.05	0.86	3.23	0.88	2.95	0.96
Flood days	26.0	16.0	24.8	15.3	29.5	18.9	24.5	14.4	24.3	14.0
Affected rice farm (%)	0.89	0.23	0.82	0.26	0.90	0.23	0.93	0.19	0.88	0.26
Rice income lost (%)	0.68	0.29	0.68	0.36	0.75	0.27	0.58	0.26	0.71	0.26
Consumption lost (%)	0.08	0.14	0.06	0.13	0.08	0.13	0.10	0.15	0.09	0.15
Rice income lost ($)	1,648	6,150	1,459	1,693	1,209	4,425	579	599	3,425	11,050
Asset lost ($)	163	1,054	119	189	104	291	27	53	408	2,063
With house damage (%)	0.07	0.25	0.00	0.00	0.13	0.34	0.04	0.20	0.07	0.25
With productive asset lost (%)	0.34	0.47	0.42	0.50	0.28	0.45	0.24	0.43	0.43	0.50
With member lost (%)	0.01	0.10	0.00	0.00	0.04	0.19	0.00	0.00	0.00	0.00
With reduced consumption (%)	0.24	0.43	0.24	0.44	0.28	0.45	0.16	0.37	0.28	0.46
With reduced schooling (%)	0.09	0.28	0.09	0.29	0.09	0.29	0.08	0.28	0.09	0.28
With reduced health care (%)	0.15	0.36	0.12	0.33	0.26	0.44	0.10	0.31	0.09	0.28
	All		Prey Veng		Kampong Thom		Banteay Meanchey		Battambang	
C. Coping strategies	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Forest clearance	0.05	0.22	0.06	0.24	0.06	0.23	0.04	0.20	0.04	0.21
Collect forest product/fishing	0.39	0.49	0.36	0.49	0.43	0.50	0.43	0.50	0.33	0.47
Asset sale	0.30	0.46	0.45	0.51	0.37	0.49	0.24	0.43	0.17	0.38
Drawing out saving	0.24	0.43	0.27	0.45	0.26	0.44	0.22	0.42	0.20	0.40
Child labor	0.10	0.30	0.03	0.17	0.07	0.26	0.12	0.33	0.15	0.36
Adult labor	0.27	0.45	0.09	0.29	0.31	0.47	0.33	0.47	0.30	0.47
Borrowing from banks	0.10	0.30	0.15	0.36	0.15	0.36	0.02	0.14	0.09	0.28
Borrowing from MFIs, groups	0.19	0.57	0.30	0.72	0.22	0.62	0.14	0.51	0.11	0.43
Borrowing from friends/relatives	0.06	0.24	0.00	0.00	0.09	0.29	0.08	0.28	0.04	0.21
Borrowing amount ($)	586	836	1,187	1,117	345	489	347	415	609	1,027
Remittances	0.13	0.34	0.03	0.17	0.22	0.42	0.16	0.37	0.07	0.25
Governments	0.15	0.36	0.09	0.29	0.35	0.48	0.04	0.20	0.07	0.25
NGOs	0.19	0.39	0.09	0.29	0.39	0.49	0.06	0.24	0.15	0.36

Flood height = 1 if very little, = 2 if knee high = 3 if chest high = 4 if above chest high. Coping strategies reported as percent of flooded households using the strategies.

Figure 4.1 shows our survey villages in the four provinces overlaid with the 2011 flood map. Prey Veng is located in the southeastern plain on the crossing of the Upper Mekong and Lower Mekong rivers, the two major rivers in Cambodia. With annual flow of water from both rivers, the province is one of the high-potential agricultural zones of the country. Apart from rice, farmers often diversify into other high-potential cash crops. The province also has good access to market and financial services due to its close proximity to the capital city, Phnom Penh. The other three provinces are located in the Tonle Sap Biosphere Reserve, meaning people there also greatly rely on the forest and natural resources for their livelihoods. Kampong Thom is located on the eastern floodplain of Tonle Sap lake and occupies key core biodiversity areas in the reserve. The province is among the largest in the country, so people have good access to employment and financial services. Banteay Meanchey occupies the extended lowland floodplain of Tonle Sap lake in the northwest. The province also has a border with Thailand and its people benefit from cross-border labour migration opportunities. Battambang is the country's largest rice production province in Cambodia and its rice is predominantly a high-yielding variety. The province also serves as a commercial and tourist hub in the northwestern region, with extended market access and alternative livelihoods, making the province wealthier than the other three.

The 2011 mega flood posed a serious challenge to development and the livelihoods of people in all these four rice-growing provinces. The variations of flood experience across the four provinces are shown in Panel B of Table 4.1. Since the 2011 flood had resulted from the overflow of rainwater from the Mekong River toward Tonle Sap lake, it hit Prey Veng slightly earlier, in late August, before continuing to Kampong Thom, Banteay Meanchey, and Battambang in early September. Flood heights were also different with the majority of households in Prey Veng experiencing knee-high flood, whereas the other three provinces in the Tonle Sap region experienced chest-high flood.

Households also reported the number of days that their rice fields were completely submerged by floodwater. We used this information to generate the total number of days that each household experienced the 2011 flood.[9] On average, the mega flood resulted in 26 submerged days, with a maximum of 180 days experienced in Kampong Thom. The mega flood damaged 89 percent of rice fields and resulted in an average of USD 1,648 lost in rice income and USD163 lost in assets in the four provinces, per household. The largest loss

[9] We note that rice fields are typically located in lower land rather than in residential areas. If the housing areas were also flooded, it is very likely that the rice fields were also and still flooded. Thus, our household flood days could potentially capture the (non-linear) intensity of the 2011 flood, especially when the flood levels were high enough to damage housing and household assets.

was suffered by the relatively wealthy rice farmers in Battambang (averaging USD3,425 rice income loss and USD408 asset loss). Among the key assets lost were livestock and productive farm assets. Only seven percent of households reported damaged housing and one percent reported having lost family members. Following the 2011 flood, 24 percent of our sampled households reported they had to reduce consumption, nine percent had to cut back on child schooling, and 15 percent on health care, with slightly greater impacts in Kampong Thom.

Panel C of Table 4.1 shows the variations of coping strategies the flooded households used during the 2011 mega flood across the four provinces. Strikingly, despite great variations, reliance on natural resources as a safety net was the most salient mechanism in all of the provinces—it was adopted by 39 percent of flooded households. Social mechanisms and reliance on assistance from the government or non-governmental organisations (NGOs) were quite limited and varied greatly across the four provinces. Specifically, 22 percent of flooded households relied on remittances and borrowing from friends and relatives, although shares varied from only three percent in Prey Veng to 31 percent in Kampong Thom. Fifteen percent of flooded households relied on the government and 19 percent on NGOs, but the bulk of such assistance was concentrated in Kampong Thom.

Apart from natural resources, our sampled rice-farming households relied more on various self-coping mechanisms—29 percent of flooded households reported using borrowing to cope with the 2011 flood, more than half of which borrowed from informal institutions such as microfinance institutions and saving groups. Use to credit to cope with the flood also varied across provinces, ranging from 45 percent in Prey Veng, 37 percent in Kampong Thom, 20 percent in Battambang, to 16 percent in Banteay Meanchey. Savings were used by some 24 percent of affected households and 27 percent of flooded households, especially in the three provinces in the Tonle Sap region, used additional labour income to cope with the 2011 flood. Despite the variety of strategies available, the use of "destructive" strategies, e.g., asset sales and child labour, were also common in some provinces.

Overall, the above statistics suggest (i) significant and varying impacts of the 2011 flood on rice-farming communities in Cambodia; (ii) the importance of natural resources as a safety net during the mega flood; (iii) a striking limit to social and government/NGOs assistance during the flood; and (iv) the great extent and variety of self-coping mechanisms used by flooded Cambodian farmers during the flood. These varying flood experiences, opportunities and limits to the use of various mechanisms among affected households, therefore, could affect preferences, subjective expectations and behavioural choices.

2.2. The 2011 flood exposures

Our sampling strategy discussed above allows us to construct three flood exposure variables. First, village-level flood exposure is a binary variable indicating whether the household was in a (relatively more severely) flooded village in 2011, where flooded village is defined as a village with a majority of areas flooded for more than 15 days and/or a village with more than 50 percent of households reporting rice production loss due to the flood. Employing this flood variable, our estimations should be able to identify the potential (marginal) impacts on households living in severely flooded villages relative to those living in not so severely flooded villages. Thus, the estimated impacts should generally include overall effects including likely spillover and general equilibrium effects on non-flooded households in these severely flooded villages. We note that our estimates could still suffer from the likely spillover effects within the flooded commune, district, province, or even country. But with village-level flood exposure, spillover effects at the higher levels should bias our results toward finding no effect.

Second, household-level flood exposure is another binary variable indicating whether a household was flooded in 2011 (i.e., when their rice fields were completely submerged by floodwater for more than 15 days). Employing this household-level flood variable, our estimations should be able to identify the potential impacts on households directly hit by the 2011 flood. However, estimated impacts could still suffer from likely spillover effects, which again should bias out results toward finding no effect.

Finally, we also used the number of days that households' rice fields were completely submerged by floodwater to capture continuous household-level flood intensity. Our estimations using this flood variable should identify the potential heterogeneous effect of different levels of flood intensity on flooded households. Altogether, these three variables should capture the varying aspects of the 2011 flood experienced by Cambodian rice-farming households.

2.3. The Survey

The fieldwork conducted in April 2014 includes a standard household socioeconomic survey with detailed questions on the 2011 flood experience, other risks experienced by households over the past 10 years, risk management strategies, as well as key behavioural choices related to farm investment, saving and other safety net behaviours. The fieldwork also included a series of hypothetical experiment questions to elicit risk, time, social preferences; subjective expectations of future floods and resulting income loss; and household perceptions of the reliability of various safety net institutions to protect against the impacts of future floods. Appendix 1 provides a summary of the experiments and the associated preference parameters.

First, for risk preference, we replicated the simple Binswanger (1980) game by allowing respondents to choose different rice seed types with different degrees of risk and return. Respondents' seed choices could thus reflect their degree of risk aversion. We then constructed our risk aversion variable as a scaling indicator ranging from 1 (least averse) to 5 (most averse).

Second, for time preference, the experiment consisted of a series of seven questions, each asking a respondent to choose between the choice of receiving some amount of money now or receiving a larger amount (that kept increasing as the experiment progressed from questions 1 to 7) in the future if he or she could wait to receive it. Observing the patterns of answers to these seven questions—specifically the first time when the respondent chose to accept the payment in the future—could reflect the extent to which respondents discount the future over the present, i.e., the degree of impatience. We then construct our impatience variable as a scaling indicator ranging from 0 (not impatient) to 8 (most impatient). [10]

[10] We note that our simple measure of time preference is subject to risk aversion, as preferring to accept lower instantaneous payment to higher future payment may reflect an aversion to future payment that could be perceived as risky, in addition to time impatience.

Third, for social preference, we used a dictator game to illicit measures of household's altruism. Each respondent was given some amount of money, all or part of which they could give to a randomly chosen household in their village. The respondent was also told that the chosen beneficiary would be anonymous and that the respondent's decision would be kept confidential. We repeated this game but changed the beneficiary to be a randomly chosen flood-affected household in their village. We then constructed our altruism variable for each game from the proportion (0-100 percent) of money respondent chose to give.

Fourth, in our experiments on subjective expectations we asked each respondent to assign probabilities to future flood events. We used 10 coins as visual aids to express the probability concept[11] and asked each respondent to place the coins in front of each of three flood events (no flood, mild flood, and mega flood), where the number of the coins he/she put would reflect the likelihood he/she thought each event would occur in the next 10 years. Before we began the exercise, our enumerator first clarified the definition of mild flood—i.e., a flood event with less than knee-high floodwater and fewer than 10 days of waterlogging in the farm—and the definition of severe flood—i.e., a flood event with more than knee-high floodwater or more than 10 days of waterlogging in the farm—and explained the exercise, using several examples (see Appendix 1). We repeated this exercise to also elicit the respondents' perceptions of the likely proportion of rice income loss and the reliability of various safety nets conditional on the occurrence of mild and severe floods in the future. We then constructed each respondent's subjective expectation variables directly from the number of coins he/she assigned to each event.

Finally, we also used a general social science survey to elicit the degrees to which each respondent trusted family, neighbours, businesses and local governments. These questions allowed us to construct series of binary trust variables.

[11] Visual aids such as ours have been used widely in low-income countries with relatively illiterate subjects who may find direct questions about probability too abstract. See Delavande, *et al*. (2011) for a review.

2.4. Summary statistics of sampled households

Table 4.2 reports descriptive statistics of the sampled households by village and household-level flood exposure at the time of the survey in April 2014. Overall, household and village characteristics were similar for flooded versus non-flooded villages, and especially for flooded versus non-flooded households. The average household size was about five people. Seventy-eight percent of respondents in the flooded households had primary education, 32 percent had secondary education and these statistics were not significantly different for non-flooded households. Average land owned was 0.53 hectare for flooded households with a mean income per capita of USD701.62 per year, 47 percent of which came from rice production. About 23 percent of flooded households were classified as poor according to the Identification of Poor Household Program (ID Poor) and had faced about 2.3 other shocks over the past 10 years. Again, these statistics were similar for the non-flooded group. Availability of key village infrastructure and public programmes also appeared similar across flood groups.

Table 4.2 also shows some characteristics that were significantly different between the flooded and non-flooded villages—e.g., gender of the respondents, household size and land per capita. We constructed a flood-prone variable from the frequency of floods reported by each household—and so a household was prone to floods if it reported at least two floods experiences in the past five years. Our statistics also shows that flooded households were significantly more flood-prone than non-flooded households, with an average flood frequency of 1.75 in the past five years. If the key characteristics we found to be different across flood groups were also correlated with our behavioural outcomes of interest, this could potentially bias our estimation results. It is important, therefore, that we control for these variables in our empirical analysis.

Table 4.2: Summary Statistics of Sampled Households by Flood Exposure

	Village flood (=1)			Household flood (=1)		
	Flooded	Not flooded	Difference	Flooded	Not flooded	Difference
Household characteristics						
Female (=1)	0.344	0.492	-0.148***	0.436	0.380	0.056
	(0.477)	(0.502)	(0.061)	(0.497)	(0.488)	(0.065)
Age	48.82	50.33	-1.51	48.96	50.82	-1.860
	(12.29)	(13.04)	(1.583)	(12.70)	(12.57)	(1.685)
Have education-primary (=1)	0.844	0.734	0.109**	0.779	0.809	-0.030
	(0.365)	(0.443)	(0.051)	(0.416)	(0.395)	(0.054)
Have education-secondary (=1)	0.359	0.297	0.063	0.319	0.345	-0.025
	(0.482)	(0.459)	(0.059)	(0.467)	(0.478)	(0.062)
Household size	5.383	4.945	0.438**	5.174	5.142	0.032
	(2.238)	(1.652)	(0.245)	(2.070)	(1.777)	(0.263)
Member migrate (%)	0.703	0.570	0.133	0.674	0.559	0.115
	(1.159)	(0.945)	(0.132)	(1.069)	(1.033)	(0.140)
Female member migrate (%)	0.297	0.219	0.078	0.279	0.214	0.065
	(0.656)	(0.485)	(0.072)	(0.605)	(0.516)	(0.076)
Age of migrating members	16.77	15.29	1.48	17.06	13.90	3.160
	(27.97)	(25.52)	(3.347)	(27.24)	(25.67)	(3.560)
Income per capita ($)	689.81	624.79	65.02	701.62	566.53	135.09
	(903.81)	(2060.68)	(198.88)	(1874.43)	(706.81)	(211.67)
Rice income in total income (%)	0.454	0.471	-0.017	0.473	0.522	-0.049
	(0.349)	(0.357)	(0.044)	(0.345)	(0.361)	(0.046)
Land per capita (ha)	0.603	0.479	0.124*	0.532	0.558	-0.026
	(0.774)	(0.506)	(0.081)	(0.684)	(0.595)	(0.087)
Asset per capita ($)	2575.12	2270.55	304.57	2180.40	2466.35	-285.95
	(3700.23)	(2284.54)	(384.23)	(2775.34)	(3625.33)	(410.78)
ID poor household (=1)	0.219	0.250	-0.031	0.232	0.238	-0.006
	(0.415)	(0.434)	(0.053)	(0.423)	(0.428)	(0.056)
Flood prone (=1)	0.539	0.602	-0.063	0.627	0.452	0.175***
	(0.500)	(0.491)	(0.061)	(0.484)	(0.500)	(0.065)
Flood frequency in the past 5 yrs	1.625	1.516	0.109	1.750	1.202	0.548***
	(0.774)	(0.763)	(0.096)	(0.612)	(0.915)	(0.096)
Other shocks in the past 10 yrs	2.461	2.305	0.156	2.373	2.607	-0.234
	(1.674)	(1.829)	(0.219)	(1.651)	(1.932)	(0.232)
Village characteristics						
Have irrigation system (=1)	0.436	0.412	0.024	0.421	0.430	-0.009
	(0.516)	(0.466)	(0.057)	(0.459)	(0.470)	(0.061)
Have electricity (=1)	1.000	1.000	0.000	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
With social land concession (=1)	0.109	0.085	0.024	0.110	0.071	0.039
	(0.313)	(0.281)	(0.037)	(0.314)	(0.259)	(0.039)
With health equity fund (=1)	0.190	0.207	-0.017	0.191	0.177	0.014
	(0.409)	(0.322)	(0.046)	(0.394)	(0.311)	(0.049)

Standard deviations in parentheses. * p<0.1; ** p<0.05; *** p<0.01

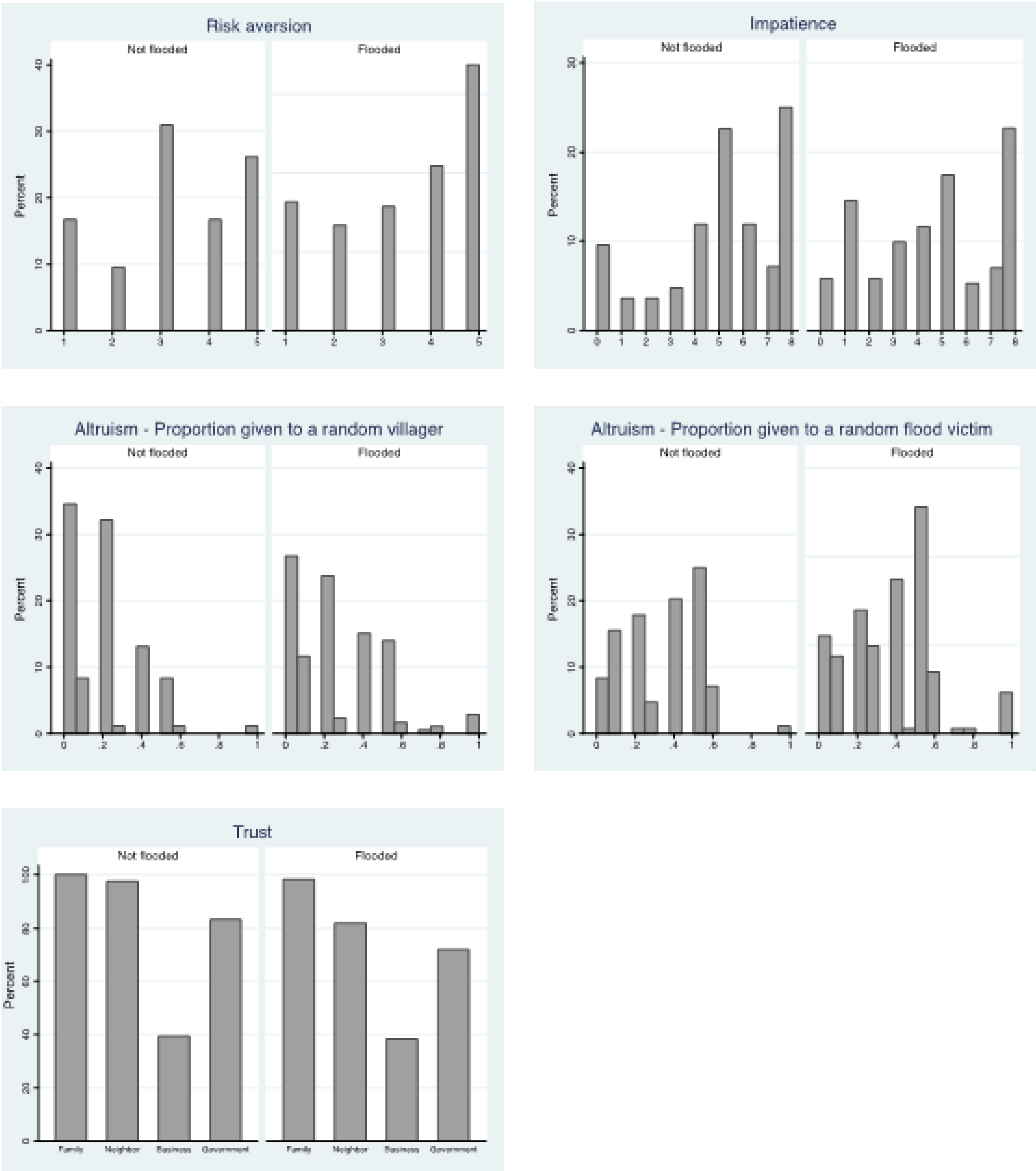
Table 4.3 reports descriptive statistics of our measures of preferences, subjective expectations, and behavioural choices, again, at the time of the survey in April 2014. The table shows that the sampled households were relatively risk averse with both the mean and the median measures of risk aversion ranging from 3.3–3.4 in all groups. Our simple comparison showed that the mean risk aversion variables were not significantly different between flooded and non-flooded villages or households. Figure 4.2 plots distributions of the risk aversion parameter by household flood experience. These plots provide the additional finding that the share of households with extreme risk aversion appeared larger among the flooded households.

Table 4.3: Summary Statistics of Preference and Behavioral Variables by Flood Exposure

	Village flood (=1)			Household flood (=1)		
	Flooded	Not flooded	Difference	Flooded	Not flooded	Difference
Preferences						
Risk aversion (1,2,..,5)	3.367	3.375	-0.008	3.424	3.261	0.163
	(1.473)	(1.425)	(0.181)	(1.474)	(1.389)	(0.192)
Impatience (0,1,2,..,8)	4.718	4.671	0.047	4.511	5.071	-0.560*
	(2.635)	(2.593)	(0.326)	(2.643)	(2.511)	(0.346)
Altruism - percent money given to randomly matched	0.259	0.201	0.058**	0.252	0.191	0.061**
villager (0-1)	(0.239)	(0.202)	(0.027)	(0.234)	(0.192)	(0.029)
Altruism - percent money given to randomly matched	0.380	0.323	0.057**	0.364	0.326	0.038*
flood victim in the village (0-1)	(0.245)	(0.192)	(0.027)	(0.232)	(0.198)	(0.030)
Trust family (=1)	0.992	0.984	0.008	0.982	1.000	-0.018
	(0.088)	(0.124)	(0.013)	(0.131)	(0.000)	(0.014)
Trust neighbor (=1)	0.875	0.867	0.008	0.819	0.976	-0.156**
	(0.332)	(0.340)	(0.042)	(0.385)	(0.153)	(0.043)
Trust business/trader (=1)	0.429	0.343	0.086*	0.383	0.392	-0.009
	(0.496)	(0.476)	(0.060)	(0.487)	(0.491)	(0.065)
Trust local government (=1)	0.773	0.742	0.031	0.720	0.833	-0.112**
	(0.420)	(0.439)	(0.053)	(0.449)	(0.374)	(0.056)
Subjective expectations						
Probability of mild flood (0-1)	0.393	0.409	-0.016	0.411	0.380	0.031
	(0.228)	(0.225)	(0.028)	(0.224)	(0.230)	(0.030)
Probability of severe flood (0-1)	0.413	0.384	0.029	0.437	0.319	0.118***
	(0.262)	(0.262)	(0.032)	(0.263)	(0.244)	(0.034
Probability of loss when mild flood occurs (0-1)	0.328	0.306	0.022	0.362	0.226	0.135***
	(0.282)	(0.285)	(0.035)	(0.291)	(0.243)	(0.036)
Probability of loss when severe flood occurs (0-1)	0.729	0.743	-0.014	0.776	0.654	0.122
	(0.286)	(0.260)	(0.034)	(0.222)	(0.342)	(0.035)
Can rely on govnt. when mild flood (=1)	0.128	0.137	-0.009	0.138	0.121	0.017
	(0.232)	(0.220)	(0.028)	(0.226)	(0.226)	(0.030)
Can rely on govnt. when severe flood (=1)	0.283	0.301	-0.018	0.294	0.288	0.006
	(0.310)	(0.300)	(0.038)	(0.295)	(0.326)	(0.040)
Can rely on social network when mild flood (=1)	0.127	0.171	-0.045*	0.179	0.089	0.090***
	(0.260)	(0.272)	(0.033)	(0.297)	(0.176)	(0.035)
Can rely on social network when severe flood (=1)	0.134	0.175	-0.041*	0.170	0.123	0.046*
	(0.237)	(0.280)	(0.032)	(0.275)	(0.222)	(0.034)
Can rely on natural resource when mild flood (=1)	0.368	0.328	0.04	0.361	0.322	0.039
	(0.372)	(0.350)	(0.045)	(0.351)	(0.382)	(0.048)
Can rely on natural resource when severe flood (=1)	0.319	0.279	0.04	0.306	0.285	0.021
	(0.345)	(0.306)	(0.040)	(0.328)	(0.322)	(0.043)
Behavioral choices						
Investment in land and irrigation (=1)	0.140	0.117	0.023	0.122	0.142	-0.020
	(0.349)	(0.322)	(0.042)	(0.328)	(0.352)	(0.044)
Have saving (=1)	0.188	0.188	0.000	0.244	0.071	0.173***
	(0.392)	(0.392)	(0.049)	(0.433)	(0.259)	(0.051)
Number of dependable friends	0.625	0.508	0.117	0.529	0.643	-0.114
	(1.049)	(0.822)	(0.118)	(0.933)	(0.965)	(0.126)
Collect forest products and fishing (=1)	0.086	0.109	-0.023	0.076	0.143	-0.067**
	(0.281)	(0.313)	(0.037)	(0.265)	(0.352)	(0.394)
Demand market insurance (=1)	0.094	0.086	0.007	0.110	0.048	0.063**
	(0.293)	(0.281)	(0.035)	(0.314)	(0.214)	(0.038)

Standard deviations in parentheses. * p<0.1; ** p<0.05; *** p<0.01

Figure 4.2: Risk Aversion, Impatience, Altruism and Trust by Household Flood Exposure



The impatience variable appeared similar between households in flooded versus non-flooded villages. Our simple comparison, however, shows that flooded households seemed to be significantly less impatient than non-flooded households. Figure 4.2 further shows that the share of households with extreme impatience appeared smaller among flooded households than among the non-flooded group.

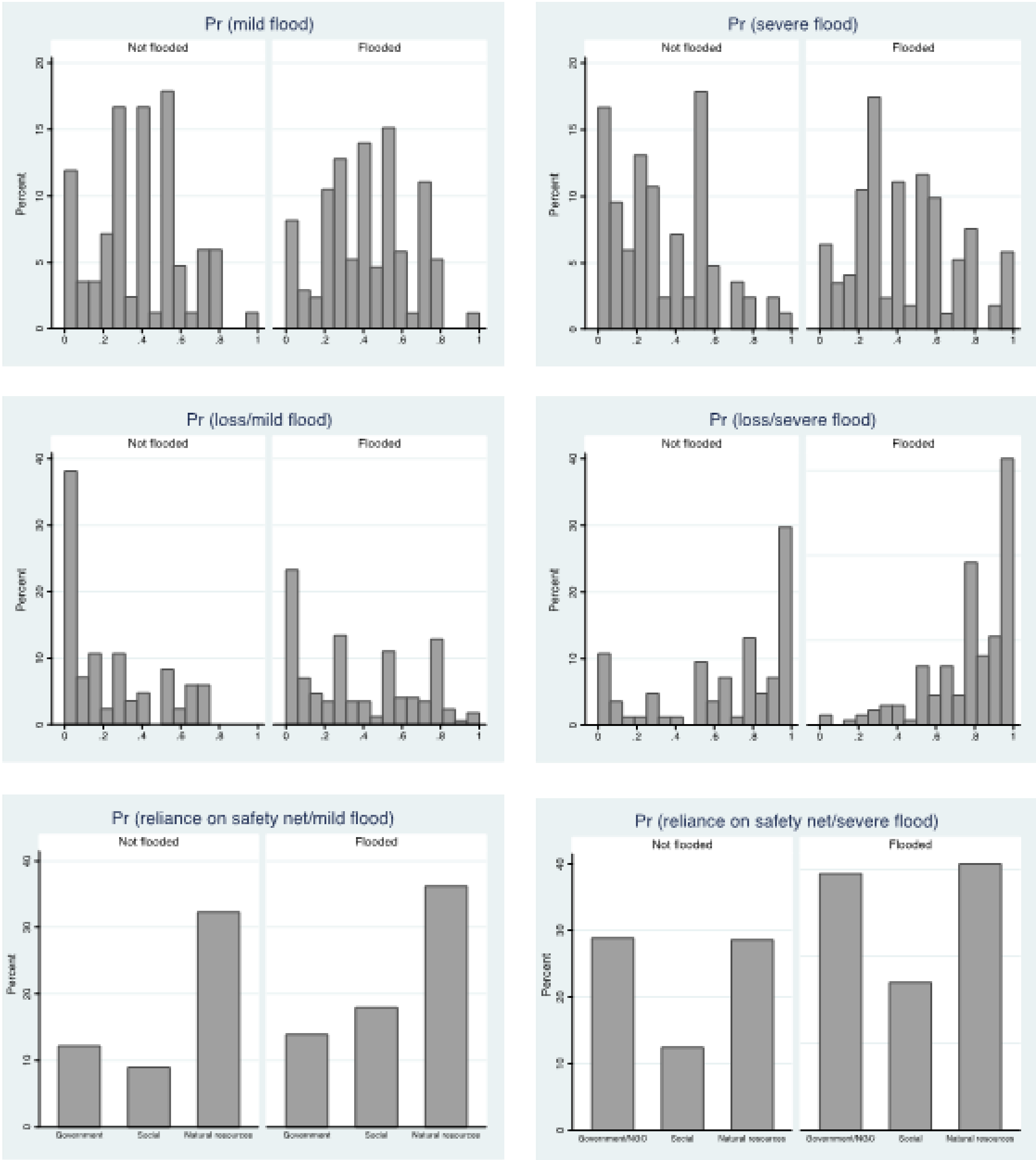
On average, there appeared to be significantly larger altruism variables for flooded households and households in flooded villages than for non-flooded groups. The average share of money given to a randomly matched villager was about 0.25 in the flooded group. As shown in Figure 4.2, a smaller share of households gave nothing but a larger share of households gave a large amount to a random villager in the flooded group than that of the non-flooded group. And in all groups, the proportion given to a random villager was smaller than that given to a flood victim.

For trust, we found that in all groups almost all (99 percent) of our sampled households trusted family, followed by trusting neighbours (82-98 percent), trusting local governments (72-83 percent) and trusting businesses (34-43 percent). The share of households that trusts family and businesses appears similar across flood groups, whereas the share of those trusting neighbours and local government appears significantly smaller in the flooded group.

For subjective expectations, our sampled households assigned large probabilities of flood risk in general (0.38-0.41 for mild flood and 0.32-0.44 for severe flood). This was to be expected given that our samples are all from flood-affected communes. The flooded households, however, assigned significantly higher subjective probabilities to severe flood, and also a significantly higher perceived proportion of rice income loss in the event of a mild flood.

Finally, the descriptive statistics of households' perceptions on safety net institutions also revealed some interesting results among our sampled rice-farming households. For both mild and severe floods, the largest percentage of households (27-37 percent) in all groups perceived that they could rely on natural resources as a safety net. These were followed by a perceived ability to rely on governments (28-30 percent) and social networks (12-17 percent) when a severe flood occurs. For mild flood, however, both perceived ability to rely on governments and social networks appeared to be similar, at only 12-13 percent. Statistically, these safety net perceptions were not significantly different across flood groups, except for the perceived ability to rely on social networks. Similar findings are depicted in Figure 4.3.

Figure 4.3: Subjective Expectations by Household Flood Exposure

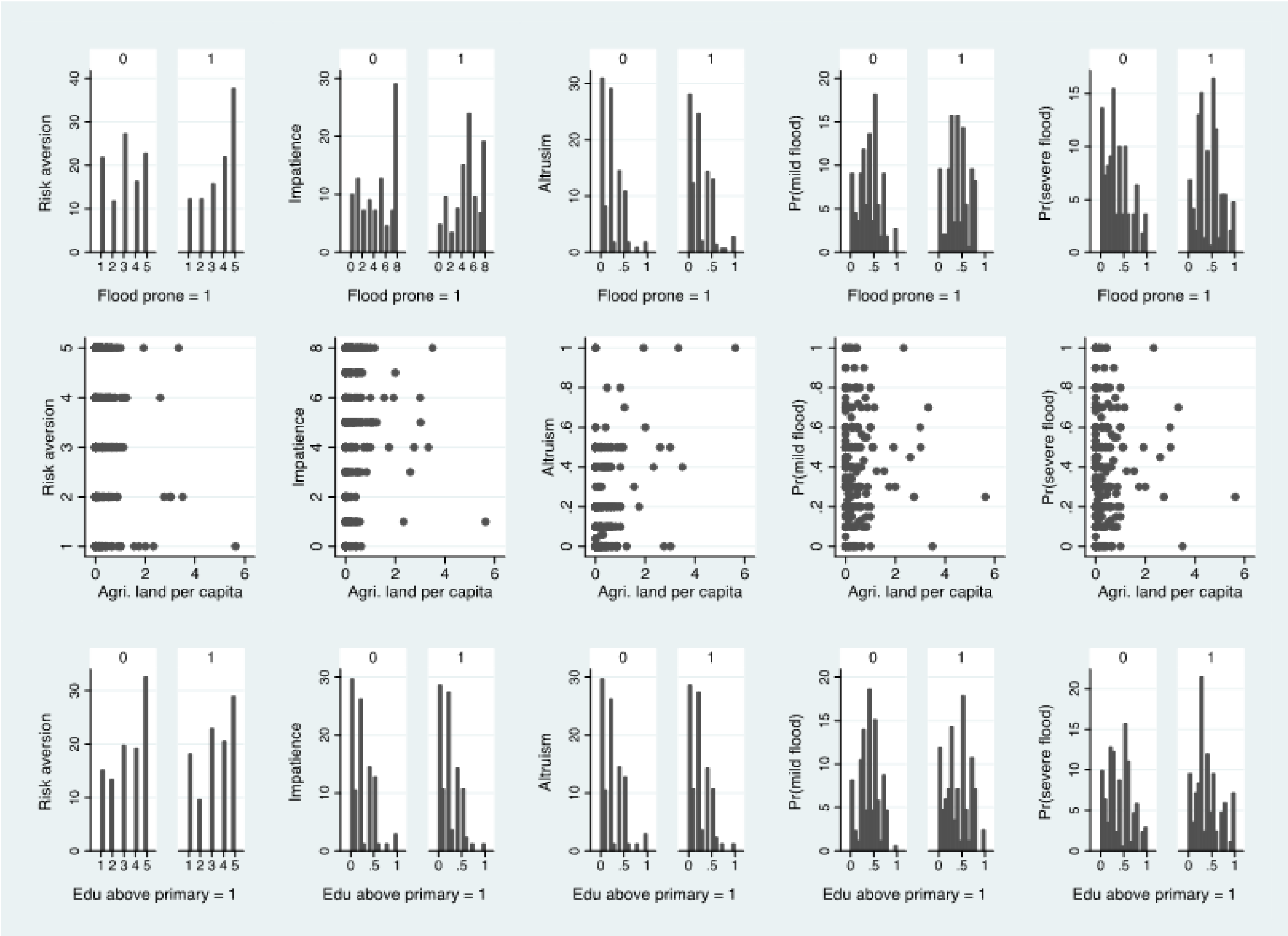


We are also interested in the potential impacts of the 2011 mega flood on some key behavioural choices that could potentially determine households' economic growth and their resilience to future floods. The variables of our interest are (i) whether a household invested in land and irrigation; (ii) whether a household had savings; (iii) the number of dependable friends a household had (as an indicator of social capital formation); (iv) whether a household collected forest products and engaged in fishing; and (v) a household's willingness to pay for commercial flood insurance. Interestingly, Table 4.3

reveals that a significantly larger percentage of households had savings and demand for commercial insurance, and a significantly smaller percentage of households collected forest products among flooded households than among non-flooded households.

These bivariate relationships in Table 4.3, however, should be interpreted with some caution. To what extent might these relationships be driven by other observed and/or unobserved variables that were correlated with both 2011 flood exposure and our outcome variables? Figure 4.4 depicts some bivariate relationships between our preference and expectation variables and (i) whether a household was flood-prone; (ii) land ownership; and (iii) education—the key covariate theoretically known to affect these behavioural variables. As expected, these figures suggest that risk aversion was positively associated with the degree of flood risk and negatively associated with wealth and education. Altruism also appeared to increase with flood risk and wealth. And the subjective probabilities of future floods were also positively associated with the degree of flood risk. Since some of these key variables were also correlated with flood exposure (e.g., flood-prone and land ownership), we will control for these variables in our estimations in the next section.

Figure 4.4: Relationships between Preferences and Key Characteristics



3. Empirical Strategy

We estimate the potential impacts of the 2011 mega flood by regressing our preference and behavioural variables on flood exposure, controlling for individual, geographical characteristics, and village fixed effects. Our estimations thus follow a simple specification:

$$y_{iv} = \beta_0 + \beta_1 Flood_{iv} + \beta_2 Flood_{iv} Floodprone_{iv} + \beta_3 X_{iv} + \alpha_v + \varepsilon_{iv}$$

where y_{iv} represents preference, subjective expectation, or other behavioural choice variables of interest. $Flood_{iv}$ is a variable that captures households' exposure to the 2011 flood. In our analysis, we use three different measures of this flood exposure: (i) a village-level indicator if a household was in the flooded village, utilising the exogenous variation of flood experience across villages; (ii) a household-level indicator if a household was directly affected by flood, utilising exogenous variations of flood experience across households within each village; and (iii) the number of days that a household's rice fields were completely submerged by floodwater, capturing the continuous household-level flood intensity. $Floodprone_{iv}$ is a household-level indicator variable controlling for the potential lurking effect of the degree to which each household was prone to floods.[12] X_{iv} are various household-level controls while α_v controls for unobserved heterogeneity at village level.[13] We also clustered all specifications at the commune level.

Various potential sources of selection bias are worth discussing. First, one would wonder if the variations of village-level flood experience were exogenous. Since the flood-prone villages were likely be flooded, the flood-prone variable would be correlated with some key behavioural variables. To address this concern, we stratify our sample by their vulnerability to flood, captured by the flood-prone variable, and control for this in the estimation. Another potential problem is migration, which could generate an endogeneity in flood exposure, especially if many households moved from flooded to non-flooded areas. However, this problem should be minimal for our sampled

[12] Again, flood-prone equals one if household had experienced at least two floods over the past five years.
[13] For village flood exposure, commune level fixed effect was used.

households—their lands were largely inherited if they owned and/or relied on community land, making mobility difficult. There is also a problem of changes in household composition between the time of the 2011 flood and the time of the survey in 2014. This problem resulted not only from demographic changes (unlikely due to the short time frame), but also from seasonal migration of household members as a consequence of the 2011 flood. Again, this problem should be negligible as Table 4.2 shows that the share of migration and the characteristics of migrants were similar between the two village groups. Likewise, Table 4.2 shows no significantly different characteristics of both households and villages between the flooded and non-flooded groups.

Moreover, there is a concern as to whether the variation of household-level flood experience was exogenous. First, there are factors determining growing patters that are correlated with flood exposure and damages, e.g, geography, irrigation, and market demand in the high demand zone like Battambang. To address this issue, we will control for village fixed effects (in addition to flood-prone indicator) in our analysis. Second, even within the same village, other factors creating the variation in household's experience of the 2011 mega flood such as the choice of rice production cycle (including harvest time), rice varieties (including deep-water varieties of rice), and the damage from the flood were correlated. However, we argue that the rice production cycle was unlikely to be endogenous to the 2011 flood. In particular, even advanced farmers found it difficult, if not impossible, to adjust their growing period to reduce flood risk in 2011 since the flood with this severity was very much unexpected when it arrived. When we asked whether households had done anything to prepare for this 2011 flood, the majority of households responding they had not. Finally, although we would expect that farmers in the flood-prone areas are more likely to adopt the flood-resistant varieties and hence less likely to be affected by the 2011 mega flood, this endogeneity should bias our results toward finding no effect of the 2011 mega flood on the flooded households.

4. Empirical Results

4.1 How did the 2011 mega flood affect preferences?

Table 4.4 summarises the regression results of the 2011 flood on households' risk aversion. Columns (1) to (3) report various ordinary least squares (OLS) regressions of risk aversion on village-flood exposure. Overall, controlling for commune fixed effect, we found no significant relationship between living in severely flooded villages and risk aversion even when controlling for the degree of flood-prone and other key covariates. Columns (4) to (7) report various OLS regressions of risk aversion on household-level flood exposure. Controlling for village fixed effects and whether a household was in a flood-prone area, column (5) shows a significant positive effect of the 2011 flood on risk aversion among flooded households in non-flood-prone areas. This result was also robust when we added a full control of other covariates. Specifically, column (6) shows that being affected by the 2011 flood resulted in a 0.39 percentage point increase in risk aversion. For flooded households already living in flood-prone areas, however, the 2011 flood did not result in statistically significant change in their risk aversion. To capture the heterogeneous impacts across wealth groups, column (7) added land per capita and flood interaction terms in the OLS regression. Interestingly, the wealth interaction term was significantly negative. These results were also robust when we performed an ordered probit regression in column (8) and when flood intensity was used in column (9). In all specifications, we also found that households living in flood-prone areas tend to have significantly higher risk aversion—0.72 percentage points higher—than those in non-flood-prone areas.[14]

[14] This finding suggests that risk aversion was not a key determinant of the choice of rice farm locations, as we would expect risk-averse farmers to choose the locations that were less prone to flood.

Table 4.4: The Mega Flood and Risk Aversion

	Village flood (=1)			Household flood (=1)					Flood days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	Oprobit	OLS
Flood	-0.008	0.185	0.274	0.133	0.422**	0.386*	0.551**	0.346*	0.013
	(0.151)	(0.280)	(0.271)	(0.220)	(0.191)	(0.201)	(0.207)	(0.202)	(0.009)
Flood*Flood prone		-0.299	-0.283		-0.634	-0.662*	-0.660*	-0.525*	-0.011
		(0.386)	(0.348)		(0.368)	(0.334)	(0.340)	(0.303)	(0.010)
Flood*Land per capita							-0.413*	-0.188	-0.026***
							(0.214)	(0.216)	(0.006)
Flood prone		0.515*	0.470		0.752***	0.726***	0.725***	0.723***	0.547*
		(0.286)	(0.297)		(0.233)	(0.236)	(0.241)	(0.255)	(0.271)
Female			0.293			0.312	0.288	0.129	0.250
			(0.209)			(0.221)	(0.224)	(0.143)	(0.216)
Age			0.001			0.002	0.002	-0.002	0.003
			(0.010)			(0.010)	(0.010)	(0.007)	(0.010)
Education-primary			-0.176			-0.090	-0.095	-0.156	-0.118
			(0.204)			(0.206)	(0.206)	(0.157)	(0.202)
Education-secondary			0.157			0.089	0.100	0.127	0.083
			(0.168)			(0.149)	(0.136)	(0.133)	(0.132)
Household size			0.032			0.021	0.022	-0.000	0.008
			(0.038)			(0.041)	(0.042)	(0.032)	(0.044)
Ln asset per capita			-0.104			-0.111	-0.124	-0.136**	-0.129
			(0.083)			(0.087)	(0.088)	(0.069)	(0.088)
Land per capita			-0.289**			-0.336***	-0.035	-0.075	0.149
			(0.124)			(0.108)	(0.181)	(0.199)	(0.140)
Number of shocks			-0.041			-0.032	-0.028	-0.019	-0.031
in the past 10 years			(0.043)			(0.043)	(0.045)	(0.045)	(0.044)
Constant	3.375***	3.065***	4.557***	3.282***	2.926***	4.606**	4.623**		4.890***
	(0.076)	(0.190)	(1.486)	(0.148)	(0.107)	(1.621)	(1.606)		(1.580)
FE	commune	commune	commune	village	village	village	village	village	village
N	256	256	256	256	256	256	256	256	256
F - Joint signt. of all flood vars		0.30	0.51		2.69	2.60	3.96	4.79	7.35

Dependent variable is risk aversion. Flood variables are indicators if household is in flooded village (1)-(3), if household was flooded (4)-(8) and number of flood days household experienced (9). Robust standard errors in parentheses clustered at commune level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Our results reveal that the impact of the 2011 mega flood on a household's risk aversion depends on whether the household was living in the flood-prone or the non-flood-prone area prior to the flood. On the one hand, for households in non-flood-prone areas, our result shows that the 2011 flood led to higher risk aversion. Our result for the Cambodian sample shows that the impact of the 2011 mega flood on risk aversion among those living in non-flood-prone areas also declined with wealth. On the other hand, for households that already lived in the flood-prone areas, the 2011 flood did not affect their risk aversion.[15]

In theory, changes in risk preference could affect household behaviours in various ways, some of which could affect economic development. For example, an increase in risk aversion could induce households to invest in more conservative projects, while an increase in risk loving behaviour may induce a higher demand for gambling and other risky behaviours, or more aggressive investment in risky ventures. Furthermore, an increase in risk aversion may generate higher demand for safety nets, through self-insurance (savings and consumption reallocation, as well as diversification of household income), market-based strategies (credit and insurance contracts), community assistance (informal assistance among family members and friends), and public assistance from the government and non-governmental organisations (NGOs). In this sense, our findings have important policy implications. For example, the resulting flood-induced reduction in risk aversion could potentially crowd in productive-yet-risky investment ventures among risk-prone flood victims. The mega flood consequently could reduce investment incentives for flood victims in the non-flood-prone region, who could become more risk averse. This adverse effect was greatest for poor flood-affected households, probably inducing them to focus on conservative investment projects with lower average returns.

Table 4.5 summarises the regression results for impatience. Columns (1) to (3) report various OLS regressions of impatience on village-flood exposure. Controlling for the commune fixed effects, we found no statistically significant relationship between living in severely flooded villages and impatience, even when we controlled for the degree of flood-prone and other key covariates. Columns (4) to (7) report OLS regressions of impatience on household-level flood exposure. Controlling for village fixed effects and whether a household

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[15] Existing literature finds inconclusive results on the impact of disasters on risk aversion. On the one hand, Cameron and Shah (2012) found that individuals who recently suffered a flood or earthquake in Indonesia exhibit higher risk aversion than individuals living in otherwise like villages. Cassar, *et al.* (2011) showed that the 2004 Indian Ocean tsunami in Thailand resulted in higher risk aversion. In particular, this finding is also consistent with the conclusions reached by Samphantharak and Chantarat (2014) who found that the 2011 mega flood in Thailand had a positive impact on risk aversion of flooded farming households. On the other hand, Page, *et al.* (2012), analysing the 2011 Brisbane flood in Australia, found that after a large negative wealth shock, those directly affected became more willing to adopt riskier options in their decision-making process.

was in a flood-prone area, as well as all covariates, column (5) to (6) show that the 2011 flood did not significantly affect impatience among flooded households. But when we added wealth interaction to the current OLS regression, we found instead in column (7) that the 2011 flood significantly reduced impatience among flooded households, and that this negative impact increased with wealth. This result was also robust when we performed an ordered probit estimation in column (8). Moreover, in almost all specifications, we found households living in flood-prone areas to have significantly higher impatience than those in non-flood-prone areas. But we found no further impact of increasing flood intensity.[16] Again, our findings have relevant policy implications. In theory, a change in time preference could affect intertemporal decisions of households such as savings. The significant increase in impatience among the flooded households could potentially affect savings, investment, and growth as households increase their current consumption at the expense of future growth through saving and investing. This effect could be especially salient among the (highly impatient) risk-prone low-wealth households, which might currently have low savings to start with.

[16] The impact of disasters on time preference in the existing literature is mixed at best. Callen (2011) showed that exposure to the Indian Ocean Earthquake tsunami affected a patience measure in a sample of Sri Lankan wage workers. Samphantharak and Chantarat (2014) found no systematic pattern of the impact on the impatience of farming households in Thailand that were affected by the 2011 mega flood.

Table 4.5: The Mega Flood and Impatience

	Village flood (=1)			Household flood (=1)					Flood days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	Oprobit	OLS
Flood	0.047	-0.242	-0.333	0.090	0.391	0.322	0.888	0.082	0.018
	(0.282)	(0.449)	(0.494)	(0.444)	(0.595)	(0.594)	(0.583)	(0.215)	(0.013)
Flood*Flood prone		0.565	0.701		-0.744	-0.732	-0.724	-0.221	0.012
		(0.715)	(0.748)		(0.505)	(0.556)	(0.546)	(0.167)	(0.017)
Flood*Land per capita							-1.425**	-0.396*	-0.036
							(0.533)	(0.227)	(0.021)
Flood prone		0.256	0.209		1.147***	1.153***	1.152***	0.257	0.371
		(0.329)	(0.326)		(0.338)	(0.377)	(0.379)	(0.196)	(0.437)
Female			0.124			0.298	0.213	0.002	0.285
			(0.419)			(0.448)	(0.454)	(0.163)	(0.449)
Age			-0.001			-0.002	0.001	0.005	0.001
			(0.014)			(0.015)	(0.016)	(0.005)	(0.016)
Education-primary			0.458			0.438	0.424	0.342**	0.402
			(0.373)			(0.360)	(0.333)	(0.139)	(0.354)
Education-secondary			0.028			0.004	0.042	-0.020	0.043
			(0.389)			(0.407)	(0.378)	(0.150)	(0.415)
Household size			-0.130			-0.152	-0.148	-0.051	-0.172
			(0.092)			(0.103)	(0.103)	(0.036)	(0.100)
Ln asset per capita			-0.070			-0.077	-0.119	-0.044	-0.085
			(0.166)			(0.176)	(0.174)	(0.056)	(0.168)
Land per capita			0.262			0.297	1.335**	0.375	0.955
			(0.387)			(0.426)	(0.543)	(0.236)	(0.607)
Number of shocks			-0.082			-0.075	-0.062	-0.058	-0.040
in the past 10 years			(0.108)			(0.106)	(0.107)	(0.042)	(0.115)
Constant	4.672***	4.518***	5.999**	4.635***	4.093***	5.779*	5.837*		5.667**
	(0.141)	(0.235)	(2.523)	(0.298)	(0.369)	(2.928)	(3.027)		(2.641)
FE	commune	commune	commune	village	village	village	village	village	village
N	256	256	256	256	256	256	256	256	256
F - Joint significant		0.32	0.44		1.23	0.97	3.65	10.78	2.88

Dependent variable is impatience. Flood variables are indicators if household is in flooded village in (1)-(3), if household was flooded (4)-(8) and number of flood days household experiened in (9). Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01

Table 4.6 summarises the regression results for altruism. We pooled the two altruism variables (proportion of money given to a random villager and to a random flood victim) and used an indicator variable “Given to flood victim” to indicate the results for the latter variable. Columns (1) to (3) report OLS regressions of altruism on village flood exposure. With full control, we found no significant effect of the 2011 flood on altruism among households living in flooded villages. Columns (4) to (7) show various OLS regression results of altruism on the household-level flood exposure variable. Controlling for village fixed effects, we found that the 2011 flood significantly increased altruistic behaviour among flooded households. Using a flood intensity variable, column (8) further shows a significantly positive effect of increasing flood intensity on the amount given to flood victims among flooded households in non-flood-prone regions.[17] Economic theory predicts that an increase in altruism may lead to a reduction in public goods exploitation and a rise in social capital. The resulting increase in altruism among Cambodian flooded households discussed above could crowd in better communities and social capital formation among flooded communities.

[17] As for studies of disasters and social preference, Castillo and Carter (2011) found that a large negative shock from Hurricane Mitch in 1998 affected altruism, trust, and reciprocity in small Honduran communities, while Cassar, *et al.* (2011) showed that the 2004 Indian Ocean tsunami in Thailand also resulted in higher altruism. However, Samphantharak and Chantarat (2014) found that the 2011 mega flood in Thailand made flooded households become less altruistic.

Table 4.6: The Mega Flood and Altruism

	Village flood (=1)			Household flood (=1)				Flood days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Flood	0.058**	0.026	0.013	0.057	0.093**	0.097**	0.125**	0.000
	(0.022)	(0.028)	(0.036)	(0.038)	(0.042)	(0.043)	(0.045)	(0.001)
Flood*Given to flood victim	-0.001	-0.001	-0.002	-0.022	-0.022	-0.022	-0.022	0.001*
	(0.032)	(0.032)	(0.032)	(0.026)	(0.026)	(0.026)	(0.026)	(0.001)
Flood*Flood prone		0.057	0.050		-0.070	-0.065	-0.070	-0.001
		(0.036)	(0.043)		(0.057)	(0.057)	(0.052)	(0.001)
Flood*Land per capita							-0.064	-0.003
							(0.053)	(0.002)
Given to flood victim	0.122***	0.122***	0.123***	0.136***	0.136***	0.136***	0.136***	0.096***
	(0.022)	(0.022)	(0.023)	(0.018)	(0.018)	(0.019)	(0.019)	(0.021)
Flood prone		-0.018	-0.013		0.058	0.054	0.054	0.037
		(0.031)	(0.037)		(0.041)	(0.038)	(0.037)	(0.028)
Female			-0.062***			-0.065**	-0.069**	-0.070**
			(0.021)			(0.023)	(0.024)	(0.024)
Age			-0.002**			-0.002*	-0.001	-0.002**
			(0.001)			(0.001)	(0.001)	(0.001)
Education-primary			-0.020			-0.021	-0.021	-0.021
			(0.029)			(0.033)	(0.034)	(0.034)
Education-secondary			-0.032			-0.031	-0.029	-0.033
			(0.026)			(0.028)	(0.027)	(0.028)
Household size			0.004			0.004	0.005	0.002
			(0.006)			(0.006)	(0.006)	(0.006)
Ln asset per capita			0.012			0.010	0.008	0.006
			(0.019)			(0.020)	(0.020)	(0.020)
Land per capita			0.050**			0.054***	0.105***	0.108***
			(0.017)			(0.018)	(0.032)	(0.034)
Number of shocks			0.009			0.012	0.012	0.011
in the past 10 years			(0.007)			(0.008)	(0.007)	(0.007)
Constant	0.201***	0.212***	0.126	0.192***	0.165***	0.076	0.079	0.203
	(0.014)	(0.018)	(0.308)	(0.023)	(0.029)	(0.340)	(0.336)	(0.329)
FE	commune	commune	commune	village	village	village	village	village
N	512	512	512	512	512	512	512	512
F - Joint significant	4.31	4.25	2.02	1.20	1.66	1.71	2.27	1.92

Dependent variable is altruism measured by percentage of money given to randomly matched villager or flood victim in the village. Flood variables are indicators if household is in flooded village in (1)-(3), if household was flooded (4)-(7) and number of flood days household experienced in (8). Tobit regressions with random effects are qualitatively similar. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

Finally, Table 4.7 summarises the regression results for trust. We first regressed the four trust variables (trust family, neighbours, businesses, and local government) on household flood exposure in columns (1) to (4) and on flood intensity in columns (5) to (8), controlling for village fixed effects and all covariates. Similar results were found in both household flood variables.[18] The 2011 flood does not affect trust of family and businesses. The flood and the increasing flood intensity, however, significantly reduced trust of neighbours and local government among flooded households. One of the reasons could be that flooded households realised the limitation of the role of local government and social risk sharing in the presence of aggregate shocks. Or the mega flood might create some conflicts within flooded communities, e.g., with respect to resources allocation or water management. The flood also resulted in a significant reduction of trust in businesses among flooded households in flood-prone areas, which, without flood, trusted this sector significantly more. To the extent that trust could determine social interactions and thus formation of social capital in the community, the resulting reduction in trust of friends among flooded households could obscure social capital formation in the affected communities. The resulting reduction in trust of social networks and local government could also provide a greater incentive for households to become more self reliant in terms of risk coping and managing, including entering into insurance contracts provided by the private sector. Note that this result is not contradictory with the earlier finding that the flood led to higher altruism. While the 2011 mega flood resulted in lower trust of friends and local government, the failures of local community and government during the mega flood could in fact induce the flooded households to recognize the importance of community assistance during the time of catastrophe, hence resulting in their higher altruism.

[18] We found similar results for households living in flooded villages (i.e., when we used village-level flood exposure in the regressions).

Table 4.7: The Mega Flood and Trust

	Household flood (=1)				Flood days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Family	Neighbor	Business	Local Govt.	Family	Neighbor	Business	Local Govt.
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Flood	-0.022	-0.147***	0.101	-0.287***	-0.001	-0.003	0.003	-0.008***
	(0.014)	(0.047)	(0.067)	(0.094)	(0.001)	(0.002)	(0.003)	(0.002)
Flood*Flood prone	0.031	0.033	-0.226*	0.088	0.001	0.002	-0.006**	0.006*
	(0.021)	(0.055)	(0.113)	(0.113)	(0.001)	(0.002)	(0.003)	(0.003)
Flood prone	-0.003	0.017	0.225***	0.019	0.004	-0.011	0.195***	-0.069
	(0.007)	(0.049)	(0.074)	(0.108)	(0.027)	(0.061)	(0.064)	(0.109)
Female	-0.011	0.008	-0.132**	0.037	-0.010	0.008	-0.147**	0.042
	(0.012)	(0.059)	(0.055)	(0.066)	(0.011)	(0.061)	(0.054)	(0.066)
Age	0.001*	0.007***	-0.003	0.001	0.001*	0.007***	-0.003	0.001
	(0.000)	(0.002)	(0.003)	(0.003)	(0.000)	(0.002)	(0.003)	(0.003)
Education-primary	-0.006	0.145**	-0.291***	0.047	-0.004	0.146**	-0.299***	0.052
	(0.023)	(0.064)	(0.081)	(0.083)	(0.022)	(0.065)	(0.077)	(0.087)
Education-secondary	0.016	0.011	-0.034	-0.121	0.014	0.005	-0.037	-0.135
	(0.015)	(0.049)	(0.087)	(0.081)	(0.013)	(0.047)	(0.085)	(0.084)
Household size	0.005	0.019*	-0.020	-0.002	0.005	0.022**	-0.022	0.005
	(0.005)	(0.009)	(0.015)	(0.024)	(0.005)	(0.009)	(0.015)	(0.024)
Ln asset per capita	0.025	0.052***	0.051	-0.032	0.025	0.056***	0.052	-0.026
	(0.022)	(0.016)	(0.046)	(0.038)	(0.022)	(0.016)	(0.046)	(0.036)
Land per capita	-0.013	0.029	-0.073	-0.053	-0.013	0.030	-0.073	-0.053
	(0.010)	(0.024)	(0.050)	(0.064)	(0.010)	(0.024)	(0.049)	(0.070)
Number of shocks	0.010**	-0.013	0.027	0.038*	0.010**	-0.014	0.025	0.037*
in the past 10 years	(0.005)	(0.022)	(0.020)	(0.020)	(0.004)	(0.022)	(0.021)	(0.021)
Constant	0.525	-0.411	0.011	1.019	0.532	-0.508	0.004	0.884
	(0.361)	(0.272)	(0.708)	(0.679)	(0.388)	(0.308)	(0.743)	(0.635)
FE	village	village	village	village	village	village	village	village
N	256	256	256	256	256	256	256	256
F - Joint significant	1.27	6.11	2.01	5.07	0.48	2.02	2.71	6.45

Dependent variables are binary variable whether respondent trusts the above institutions. Flood variables are indicators if household was flooded (1)-(4) and number of flood days household experience in (5)-(8). Regressions with village level flood are qualitatively similar so as probit regressions with random effects. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

4.2. How did the 2011 mega flood affect subjective expectations of future floods, rice income loss, and reliability of various safety nets?

Table 4.8 summarises the regression results for subjective expectations of future mild flood, severe floods, and the expected proportion of rice income loss following mild or severe floods. We first pooled mild and severe flood events and used an indicator variable “For mild flood” to indicate results for the mild flood. Columns (1) and (2) report simple OLS regressions using village flood exposure; columns (3) and (4) for household flood exposure, and columns (5) and (6) for flood intensity, with fixed effects and full controls. In all specifications, we found that the subjective expectation of mild floods (proportion of rice income loss when mild floods occur) appeared significantly larger (smaller) than that of severe floods. And households living in flood-prone areas had significantly larger subjective expectations of severe flood than those in non-flood-prone areas. The effects on mild floods, however, were inconclusive across specifications. The 2011 flood significantly increased subjective expectations of future severe floods among households living in flooded villages and flooded households. The occurrence of a flood, therefore, may induce them to update their expectations. But the positive effect was smaller (and almost non-existent in some specifications) if households were already in flood-prone areas and so had already experienced regular floods. According to columns (2), (4), and (6), being in flooded villages did not affect perceptions of rice income loss when future flood occurs. Increasing flood intensity, however, was significantly associated with the expectation of increasing rice income loss from future severe floods. Overall, if subjective expectations of future floods and loss could induce investment incentives regarding flood risk management as theories predict, our positive results might imply that the 2011 mega flood experience could potentially crowd in actions that might improve resilience to future floods among affected households and communities.

Table 4.8: The Mega Flood and Subjective Expectation of Future Flood

	Village flood (=1)		Household flood (=1)		Flood days	
	(1)	(2)	(3)	(4)	(5)	(6)
	Pr(flood)	Pr(loss/flood)	Pr(flood)	Pr(loss/flood)	Pr(flood)	Pr(loss/flood)
	OLS	OLS	OLS	OLS	OLS	OLS
Flood	0.123***	0.026	0.162***	0.044	0.004***	0.003*
	(0.029)	(0.074)	(0.032)	(0.067)	(0.001)	(0.002)
Flood*For mild flood	-0.157***	0.039	-0.134**	0.049	-0.003	-0.002
	(0.053)	(0.089)	(0.056)	(0.082)	(0.002)	(0.002)
Flood*Flood prone	-0.146***	-0.057	-0.124*	0.088	-0.004***	-0.001
	(0.035)	(0.081)	(0.065)	(0.078)	(0.001)	(0.002)
Flood*Flood prone*For mild flood	0.184**	-0.000	0.115	-0.071	0.003	-0.001
	(0.077)	(0.094)	(0.106)	(0.079)	(0.002)	(0.002)
For mild flood	0.128**	-0.440***	0.122**	-0.448***	0.102**	-0.388***
	(0.045)	(0.050)	(0.047)	(0.049)	(0.035)	(0.043)
Flood prone	0.135**	0.020	0.128**	-0.082	0.138***	0.000
	(0.047)	(0.056)	(0.048)	(0.056)	(0.039)	(0.033)
Flood prone*For mild flood	-0.168**	0.003	-0.134	0.045	-0.130*	0.038
	(0.076)	(0.060)	(0.078)	(0.047)	(0.065)	(0.042)
Female	0.006	0.025	-0.002	0.017	-0.006	0.018
	(0.018)	(0.032)	(0.017)	(0.032)	(0.017)	(0.035)
Age	-0.000	0.000	-0.000	0.000	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education-primary	-0.032	-0.050*	-0.048**	-0.049	-0.050**	-0.049
	(0.021)	(0.025)	(0.020)	(0.029)	(0.020)	(0.030)
Education-secondary	0.025	0.050	0.032	0.045	0.035	0.051
	(0.024)	(0.031)	(0.023)	(0.033)	(0.023)	(0.035)
Household size	0.005	0.014*	0.007**	0.015*	0.005	0.013
	(0.004)	(0.007)	(0.003)	(0.008)	(0.003)	(0.008)
Ln asset per capita	-0.012	-0.023*	-0.006	-0.023	-0.008	-0.026*
	(0.007)	(0.012)	(0.007)	(0.014)	(0.007)	(0.013)
Land per capita	-0.014	-0.021	-0.011	-0.008	-0.011	-0.007
	(0.017)	(0.020)	(0.018)	(0.021)	(0.018)	(0.022)
Number of shocks	0.009*	0.020**	0.008	0.020**	0.008	0.020**
in the past 10 years	(0.005)	(0.009)	(0.005)	(0.008)	(0.005)	(0.008)
Constant	0.467***	0.985***	0.364***	0.957***	0.407***	0.975***
	(0.111)	(0.222)	(0.101)	(0.263)	(0.100)	(0.236)
FE	commune	commune	village	village	village	village
N	512	512	512	512	512	512
F - Joint significant	6.77	1.09	7.54	7.02	12.97	2.10

Dependent variable are subjective expectations of probability of severe and mild flood in (1), (3), (5) and probability of loss conditional on occurrence of severe or mild flood. For mild flood is a binary variable =1 if mild flood and = 0 if severe flood. Flood variables are indicators if household is in flooded village in (1)-(2), if household was flooded (3)-(4) and number of flood days household experienced in (5)-(6). Tobit regressions with random effects are qualitatively similar. Robust standard errors in parenthesesclustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

Table 4.9 summarises regression results on households' perceptions of the reliability of government, social networks, and natural resources as safety net during mild and severe floods. We regressed household perceptions on household flood exposure in columns (1) to (3) and on flood intensity in columns (4) to (6). With both flood variables in columns (1) and (4), we first found that the expectation of government help was significantly lower for mild floods relative to severe floods. This result reveals the well-known fact that emergency assistance tends to respond more to severe disasters. Households living in flood-prone areas also did not have significantly different expectations of government help from those in non-flood-prone areas. With both flood variables, the 2011 flood also did not significantly affect households' expectation of government assistance in the event of a future flood. One possible reason could be that government assistance has always been minimal and the experience during the 2011 flood did not lead affected households to update their perceptions. Columns (2) and (5) present the flood effect on households' perceptions of social networks. We found a significant reduction of households' perceptions of social networks as a safety net during future mild floods, especially among flooded households in flood-prone areas. This finding is consistent with the reduction in trust of friends among flooded households that we had already found. Again, if perceptions could affect social interactions, the mega flood could potentially crowd out social capital formation among the 2011 flood victims in the flood-prone communities. Finally, columns (3) and (6) reveal opposite results for natural resources. Our results for both flood exposure variables show that the 2011 flood caused a significant increase in perceived reliability of natural resources as a safety net during future mild floods among flooded households.[19]

[19] Again, the flood effects on households living in flooded villages are qualitatively similar, so they are not reported.

Table 4.9: The Mega Flood and Safety Net Perceptions

	Household flood (=1)			Flood days		
	(1)	(2)	(3)	(4)	(5)	(6)
	Can rely on governt when flood	Can rely on social when flood	Can rely on natural when flood	Can rely on governt when flood	Can rely on social when flood	Can rely on natural when flood
	Probit	Probit	Probit	Probit	Probit	Probit
Flood	0.374	0.228	-0.052	0.004	0.001	0.001
	(0.259)	(0.292)	(0.265)	(0.009)	(0.007)	(0.007)
Flood*For mild flood	-0.131	0.219	0.334***	-0.003	0.006	0.019*
	(0.219)	(0.222)	(0.123)	(0.009)	(0.010)	(0.010)
Flood*Flood prone	-0.479	-0.066	-0.034	-0.004	0.001	0.003
	(0.387)	(0.306)	(0.362)	(0.009)	(0.007)	(0.010)
Flood*Flood prone*For mild flood	0.328	-0.486*	-0.103	-0.001	-0.001	-0.017*
	(0.394)	(0.291)	(0.183)	(0.012)	(0.008)	(0.010)
For mild flood	-0.743***	-0.083	-0.069	-0.750***	-0.068	-0.217
	(0.175)	(0.140)	(0.115)	(0.212)	(0.175)	(0.171)
Flood prone	0.187	0.193	0.241	-0.021	0.156	0.130
	(0.272)	(0.319)	(0.317)	(0.237)	(0.273)	(0.283)
Flood prone*For mild flood	-0.170	0.018	-0.014	0.084	-0.318	0.272
	(0.264)	(0.237)	(0.136)	(0.299)	(0.228)	(0.166)
Female	-0.125	0.057	-0.109	-0.129	0.060	-0.109
	(0.164)	(0.168)	(0.207)	(0.164)	(0.177)	(0.208)
Age	-0.006	-0.017**	-0.042***	-0.006	-0.016**	-0.041***
	(0.004)	(0.008)	(0.006)	(0.005)	(0.008)	(0.006)
Education-primary	0.042	-0.500***	0.057	0.043	-0.496***	0.053
	(0.173)	(0.178)	(0.266)	(0.178)	(0.181)	(0.269)
Education-secondary	-0.093	-0.198	-0.399**	-0.102	-0.197	-0.382**
	(0.148)	(0.176)	(0.194)	(0.154)	(0.178)	(0.188)
Household size	-0.017	0.015	0.104**	-0.020	0.008	0.098**
	(0.029)	(0.032)	(0.041)	(0.029)	(0.031)	(0.040)
Ln asset per capita	-0.139*	0.019	0.098	-0.140*	0.019	0.097
	(0.080)	(0.121)	(0.094)	(0.083)	(0.123)	(0.096)
Land per capita	-0.209	-0.244	-0.119	-0.218	-0.257	-0.115
	(0.149)	(0.166)	(0.153)	(0.150)	(0.167)	(0.150)
Number of shocks	0.160**	0.098*	0.118*	0.157**	0.102*	0.124*
in the past 10 years	(0.075)	(0.052)	(0.067)	(0.076)	(0.052)	(0.068)
FE	village	village	village	village	village	village
N	512	512	512	512	512	512
F - Joint significant	2.53	5.54	16.98	1.33	3.22	7.84

Dependent variable are subjective expectations whether or not household can rely on government (1),(4),(7), on social insurance (2),(5),(8) or on natural resources (3),(6),(9) when severe or mild flood occurs. For mild flood is a binary variable =1 if mild flood and = 0 if severe flood. Flood variables are indicators if household was flooded (1)-(3) and number of flood days household experienced (4)-(6). Village flood regressions are qualitatively similar, so omited. OLS regressions with fixed effects are also qualitatively similar. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

In conclusion, on the one hand we found that the 2011 flood led to an increase in altruism, which theoretically should reduce incentives for exploitation of public goods and therefore natural resources. On the other hand, the 2011 flood also caused flooded households to upgrade their perceived reliability of natural resources as their safety net. However, these two apparently contradictory finding could be reconciled. Reduction in forest extraction now could imply that these households had increasingly used public natural resources as insurance against bad years. In this sense, households effectively view natural resources as community savings, with potential future benefits.

4.3 How did the 2011 mega flood and (updated) preferences affect households' behavioural choices?

We motivate our study from the beginning that one of the key values to understand how the mega flood affected preferences and expectations is that these changes in preferences and expectations could affect households' behavioural choices, and some of these behaviour choices could in turn affect households' long-term economic development and resilience to future shocks. We revisit our motivations in this section by analysing whether and how the 2011 flood affected households' key behavioural choices. We then explore if and how these behavioural choices were related to preferences and subjective expectations. Combining these two analyses with our earlier results, we hope to provide some insights relevant to policymakers.

Table 4.10 summarises regression results on five behavioural choices that households made during 12 months before the survey was conducted in April 2014: (i) whether households invested in land and irrigation; (ii) whether household had savings; (iii) the number of dependable friends household had; (iv) whether household collected forest products and engaged in fishing; and (v) whether households were willing to pay for commercial flood insurance. Behavioural choice (i) is critical for economic development, while behaviours (ii) to (v) reflect self, natural resource, social, and market insurance decisions, which are critical for the resilience of households in developing economies.

Table 4.10: The Mega Flood and Behavioral Choices

	Investment in land and irrigation			Have saving			Collect forest products and fishing			Number of dependable friends			Demand for market insurance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Flood	-0.157*		-0.176**	0.129*		0.091	-0.181***		-0.148**	-0.298*		-0.299*	-0.017		-0.014
	(0.080)		(0.080)	(0.061)		(0.077)	(0.055)		(0.052)	(0.159)		(0.159)	(0.071)		(0.067)
Flood*Flood prone	0.300***		0.329***	0.026		0.026	0.145		0.116	0.168		0.285	0.158**		0.120*
	(0.099)		(0.097)	(0.085)		(0.087)	(0.099)		(0.099)	(0.253)		(0.235)	(0.070)		(0.067)
Risk aversion		-0.033*	-0.032*		-0.017	-0.016		-0.002	-0.001		0.022	0.024		-0.010	-0.008
		(0.017)	(0.017)		(0.017)	(0.017)		(0.013)	(0.012)		(0.041)	(0.041)		(0.017)	(0.017)
Impatience		0.016**	0.015		-0.011	-0.011		-0.003	-0.002		0.002	0.005		-0.017**	-0.017**
		(0.008)	(0.010)		(0.010)	(0.009)		(0.010)	(0.009)		(0.021)	(0.021)		(0.007)	(0.007)
Altruism		0.338***	0.338***		0.354***	0.327***		-0.178***	-0.150**		-0.417	-0.366		0.048	0.040
		(0.099)	(0.092)		(0.080)	(0.082)		(0.058)	(0.063)		(0.305)	(0.309)		(0.094)	(0.105)
Trust family		0.047	0.005		0.410**	0.395**		0.044	0.044		0.293	0.285		0.251	0.234
		(0.087)	(0.078)		(0.176)	(0.179)		(0.100)	(0.099)		(0.211)	(0.186)		(0.152)	(0.147)
Trust neighbor		-0.030	-0.038		-0.071	-0.051		0.053	0.032		0.417***	0.378***		-0.210**	-0.204**
		(0.096)	(0.095)		(0.066)	(0.074)		(0.051)	(0.046)		(0.088)	(0.081)		(0.094)	(0.085)
Trust business/trader		0.030	0.041		-0.002	0.003		0.027	0.029		0.396***	0.404***		-0.048	-0.041
		(0.044)	(0.045)		(0.045)	(0.042)		(0.047)	(0.048)		(0.110)	(0.112)		(0.045)	(0.047)
Trust local governments		0.024	0.050		0.018	0.035		0.013	0.006		0.028	0.020		-0.008	0.005
		(0.038)	(0.037)		(0.065)	(0.068)		(0.023)	(0.025)		(0.146)	(0.142)		(0.041)	(0.043)
Sjt. prob of severe flood		-0.084	-0.015		-0.011	-0.046		-0.185	-0.139		0.341	0.430		-0.039	-0.042
		(0.099)	(0.095)		(0.087)	(0.090)		(0.125)	(0.128)		(0.377)	(0.353)		(0.106)	(0.098)
Sjt. prob of mild flood		-0.186**	-0.180**		0.374***	0.331***		0.019	0.067		0.323	0.412		-0.171	-0.181*
		(0.082)	(0.070)		(0.111)	(0.101)		(0.123)	(0.125)		(0.287)	(0.271)		(0.100)	(0.093)
Flood prone	-0.256***	-0.061	-0.269***	-0.055	-0.031	-0.059	-0.051	0.030	-0.040	0.017	0.037	-0.142	-0.110*	0.026	-0.060
	(0.072)	(0.045)	(0.070)	(0.065)	(0.044)	(0.055)	(0.090)	(0.044)	(0.094)	(0.263)	(0.159)	(0.264)	(0.056)	(0.043)	(0.057)
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
FE	village	village	village	village	village	village	village	village	village	village	village	village	village	village	village
N	256	256	256	256	256	256	256	256	256	256	256	256	256	256	256

Dependent variable are behavioral choices observed in the household data. Flood variable is whether household experienced floood in 2011. Results for flood days are qualitatively similar, so omited. Robust standard errors in parenthesesclustered at commune level. * p<0.1; ** p<0.05; *** p<0.01. Same set of control variables were used, results not reported here.

Regressing these behavioural choices on household-level flood exposure and other controls, column (1) that the 2011 flood caused a significant decrease (increase) in households' plot investments for flooded households in non-flood-prone (flood-prone) areas. These findings are consistent with what we would deduce from our flood results on risk aversion and increasing subjective expectations of future floods. Column (4) shows that the mega flood also led to a significant increase in savings among flooded households. Again, this result is very much in line with our earlier result that the flood caused a significant decrease in impatience among flooded households.

Column (7) of the table shows that the 2011 flood caused a significant reduction in the collection of forest products among flooded households. The finding is in line with the resulting increase in altruism among flooded households and growing households' perceptions of the benefit of saving natural resources as a safety net against adverse years in the future. One interpretation of these combined results could be that, as the 2011 flood increased households' perception of nature as insurance, they would realise that preserving the forest in normal years (and part of this could also be induced through increases in altruism) will allow them to depend on these resources in bad years. Another possible explanation is that the mega flood may have induced affected households to insure themselves through other means (for example, through increasing savings and greater resort to commercial insurance, to be discussed in the next paragraph), hence reducing their collection of forest products. [20]

Table 4.10 also shows that the flood also caused a significant reduction in the number of dependable friends (i.e., social capital) among flooded households, as shown in column (10). From our earlier results, this might be driven by flood-induced decreasing trust and decreasing perceived benefit of social insurance. Column (13) shows that the flood caused a significant increase in demand for commercial insurance among affected households in the flood-prone region. The finding is in line with our earlier finding of a flood-induced increase in subjective expectations of future floods. One potential explanation could be that there could be other more salient determinants of insurance

[20] We also found similar results when we used household flood intensity variables. We did not find significant results, however, when we use village flood exposure.

demand than risk aversion and expectations of risk that could be induced by the mega flood.[21]

Finally, our last research question is whether these behavioural results discussed in previous paragraphs were induced by the impact of the flood on preferences and expectations? By regressing households' behavioural choices on preference variables with full controls and village fixed effects, we obtained some key results, most of which are very much in line with economic theory. First, columns (2) and (3) show that plot investment decreased significantly with risk aversion and subjective expectations of mild floods, while it increased significantly with impatience and altruism. Second, columns (5) and (6) show that decisions to save increased significantly with altruism, trust in family and subjective expectations of future mild floods. Third, columns (8) and (9) show that the decision to exploit forest products decreased significantly with altruism. Fourth, columns (11) and (12) show that the number of dependable friends also increased significantly with the level of trust of friends and businesses. Finally, we found households' demand for commercial insurance decreased significantly with growing impatience and decreasing trust of neighbours, as shown in columns (14) and (15). Strikingly, savings decisions were not significantly associated with impatience, and insurance demand was not correlated with risk aversion, as economic theory tends to predict. One potential explanation could be that financial literacy, especially with respect to savings and insurance, could still be low among Cambodian rice farmers in our sample. This last result, however, would not jeopardise our key findings: these behavioural impacts of the 2011 floods could (at least partially) be driven by the changes in preferences and expectations induced by the flood.[22]

[21] Another possible explanation is from the supply side—the 2011 mega flood may have led to an increase in the supply of commercial insurance that allowed households to have easier access to insurance contracts provided by the private sector. This relaxed constraint on access to insurance could lead to higher participation in commercial insurance despite the lower risk aversion of the population.

[22] The flood-induced changes in saving decisions were likely (though partially) the result of increasing altruism and subjective expectation induced by the flood. And the flood-induced changes in insurance decision were also likely the result of decreasing impatience and trust induced by the flood.

5. Conclusions and Policy Implications

We hope our empirical findings contribute to existing literature on the impacts of natural disasters that mediate specifically through behavioural changes. Overall, our key empirical findings on Cambodian rice-farming households suggest that the 2011 flood—the country's biggest flood in the past decade—did affect certain key preferences, subjective expectations and key behavioural choices of households, which could further determine long-term economic livelihoods and resilience to future shocks among affected households.

Specifically, we found that the mega flood seemed to have made affected Cambodian rice-farming households more risk averse, with poor households showing the largest increase in risk aversion. The mega flood also reduced impatience and increased altruistic behaviour among affected households. Surprisingly, the 2011 flood caused a significant reduction in trust of neighbours and local government. Affected by this mega flood, flood victims were found to have further revised upwards their subjective expectations of the occurrence of future severe floods.

Our findings also reveal interesting facts about how Cambodian farmers used and perceived the reliability of government, social networks, and natural resources as safety nets for the 2011 mega flood and future floods. First, we found that reliance on governments, NGOs, as well as social networks appeared to be very small among these Cambodian rice-farming communities during the 2011 mega flood. The flood also further reduced households' perceptions of the benefit of social networks as a safety net, especially among flooded households in flood-prone regions. While the finding on the marginal roles of social insurance could become more relevant—as community risk sharing is likely ineffective in insuring covariate shocks—the limited role of and perceived reliance on the government appeared quite unique compared with other developing agrarian economies, where governments would often be viewed as the insurer of last resort among poor farmers. With limited social and public support, we thus found relatively strong evidence of self-coping and self-insurance mechanisms in Cambodian rice-farming communities, such as through savings and labour allocations. The most salient result is that we found natural resources to be the most significant sources of safety net among these communities and that the mega flood caused them to further revise upward their perceived benefit of nature as a source of safety net. These findings could reflect the fact that three out of the four severely flooded provinces we studied are located in the Tonle Sap Biosphere Reserve, where reliance on the forest appeared strong. This evidence could extend well beyond Cambodia with increasing evidence that the key biodiversity hotspots also appear to be the key disaster/climate change hotspots as well.

The 2011 mega flood also affected households' behavioural choices. We hypothesise that some of these flood effects should be mediated through their effect on deep parameters of preferences and expectations since we found significant evidence that these preferences and expectations shaped households' behavioural choices, as predicted by economic theory. First, we found the flooded households to have lower land and irrigation investment relative to their non-flooded counterparts, which could potentially be driven by increasing risk aversion and subjective expectations of future floods following the mega flood. To the extent that productive investment is critical for long-term economic growth, our findings have important implications for the potential long-term welfare impact of extreme floods (or catastrophic disasters in general).

We found that flooded households extracted fewer forest products and engage less in fishing than non-flooded households. According to our results described above, this could be due to increasing altruism among flooded households, which could have led to decreasing incentives among households to exploit public goods. Reduction in forest extraction now could also imply that these households had increasingly used public natural resources as insurance, and as they increasingly perceive the benefit of nature as insurance against future shocks, they are likely to save these natural resources for bad years. In this sense, households view natural resources as community savings, with potential future benefits. On the one hand, these results could be seen as positive as disaster-affected households' incentives to preserve natural resources might increase. But on the other hand, if natural resources have increasingly been used as insurance, the widely observed increasing frequency and intensity of disasters could jeopardise the sustainability of these resources. This finding raises some concerns—if the Cambodian households extensively use natural resources as insurance, to what extent might this crowd out other safety net institutions? Does natural resource abundance inhibit the development of the financial system? Does natural resource endowment reduce the government's incentive to invest in disaster prevention infrastructure?

We found flooded households to have fewer dependable friends than non-flooded households. According to our results described above, this could be due to falling trust and the perceived benefit of social insurance following the mega flood. Altogether, our findings thus imply that the 2011 flood could potentially crowd out social interactions and thus social capital formation in the affected communities. While social insurance might not be very effective against covariate shocks, it can be very effective in terms of idiosyncratic risk sharing. And social capital itself is critical for the functioning of the economy, society and even the rural financial system. We found that flooded households have more savings and higher demand for commercial insurance than non-flooded households. In addition to the main preferences, we found these could be driven by increasing subjective expectations of future floods and decreasing trust of friends. The reduced role of social insurance seems to crowd in increasing incentives for needy self-insurance. This could also provide some evidence that the increasingly important role of natural resources has not as yet crowded out private incentives to reduce and manage disaster risks. But do Cambodian farming households have full access to effective markets and self-insurance strategies?

It is hoped our results can contribute to public policymaking regarding the design of incentive-compatible safety nets and development interventions. The empirical results emphasise that public policies promoting effective flood risk management institutions among households could crowd in investment incentives and so really be pro-poor. Thus, public assistance and safety nets in the form of investment in flood prevention infrastructure, irrigation systems or other investments to promote alternative and more resilient livelihoods would provide longer-term economic development impacts than simple transfer programmes.

With the 2011 mega flood already renewing inducing increase incentives for self-insurance among the affected population, safety-net policies should aim to help households help themselves. This can be achieved by improving access to effective strategies, e.g., facilitate access to rice varieties that are more resistant to flood, utilisation of technology and weather forecasts to make effective adaptations to rice production, or facilitate access to various ways of diversifying crops and/or income. Our results also show that the mega flood provided a boost to households’ incentives to use the market. Policies should aim, therefore, to enhance supply of and access to saving and insurance products, and to ensure effective demand among a population with relatively low financial literacy rates. As households' valuation and incentives for using natural resources as insurance increase, policies should aim to encourage conservation and sustainable use of these resources, e.g., through forest zoning and incentivised reforestation programmes. Finally, all interventions should also be designed to rebuild social interactions and capital, which were degraded by the mega flood.

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CHAPTER 5

Time Preference, Risk and Credit Constraints: Evidence from Vietnam

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We examine empirically the effects of the environment on time preference of economic agents by using a unique household data set collected in Viet Nam. The environment includes credit constraints and loss experience in the recent past—in terms of frequency, the nature of losses and the causes of losses (types of disasters). Subjective interest rates exhibit inverted yield curves, consistent with existing results from laboratory experiments and field surveys, but are contrary to what we usually observe in financial markets. The empirical analyses indicate that recent past loss experience has a significant impact on subjective overnight interest rates. Also, we estimate Euler equations of a time-additive discounted expected utility model that admits quasi-hyperbolic discounting with a power utility. The results suggest that experience of losses from avian influenza (AI) and/or floods has an impact on time preference parameters, although the impacts are not robust when the impacts of AI or flood losses through credit constraints are taken into account, suggesting possible issues with the model specification.

1. Introduction

Time and uncertainty are two central aspects in many economic models. How we model the behaviour or the preferences that dictate the behaviour of economic agents when time and uncertainty are involved is therefore crucial. The standard approach uses the (discounted) expected utility framework, which originates from Daniel Bernoulli's formulation, although there are two distinct expected utility frameworks—the objective and subjective expected utility frameworks.[1] The objective expected utility by von Neumann and Morgenstern (1947) represents preferences over lotteries or probability distributions, while the subjective expected utility by Savage (1954) represents preferences over acts and their consequences for all states of the world, i.e., no probability distributions are given a priori. Thus, the primitives of the representations are different between objective and subjective expected utility frameworks, although the representation form itself follows Daniel Bernoulli's formulation in both cases.

In the standard discrete-time framework, preferences of an agent are represented by a time-additive discounted expected utility form such as

$$U(\mathbf{X}_t) = E\left\{ \sum_{\tau=t}^{\infty} \left(\frac{1}{1+\rho}\right)^{\tau-t} u(X_\tau) \middle| \mathcal{F}_t \right\}, \tag{1}$$

where $U(\cdot)$ is a utility function defined on an infinite random consumption stream $\mathbf{X}_t$, i.e., $\mathbf{X}_t = (X_t, X_{t+1}, X_{t+2}, \ldots)$ with X_T being consumption at time T, ρ is a discount rate, $u(\cdot)$ is a von Neumann-Morgenstern utility function, F_t is the information set (a σ-algebra) at time t and $E\{\cdot|F_t\}$ is a conditional expectation given F_t. This model assumes that the agent's time preference is completely captured by a single parameter ρ and also assumes that all uncertainty is characterised by probability, i.e., there is no Knightian uncertainty, but only risk.[2] Thus, the model breaks down either when preference is not fully represented by the time discount rate ρ or an

[1] Daniel Bernoulli's original work was published in Latin in 1738, and only translated into English in 1954 and published as Bernoulli (1954).
[2] Knight (1921) was one of the first scholars who made an explicit distinction between risk and Knightian uncertainty by referring to a probabilistic quantification of uncertainty.

expected utility representation fails. The latter case includes *ambiguity* such as the case of multiple priors as per Gilboa and Schmeidler (1989) and unawareness/unforeseen contingencies, where the structure of the state space itself is unknown.[3]

Numerous experimental studies and/or field surveys have reported that the majority of people are willing to accept (demand) a higher interest rate for loans (deposits) with shorter time to maturity and/or with smaller principal.[4] In the literature, this is interpreted as evidence against the above time-consistent discounted (expected) utility model (1), and is referred to as *present bias*. To accommodate present bias, the following *quasi-hyperbolic discounting* model shown for instance in Laibson (1998) has been introduced:

$$U(\mathbf{X}_t) = E\left\{ u(X_t) + \sum_{\tau=1}^{\infty} \beta \left(\frac{1}{1+\rho} \right)^{\tau} u(X_{t+\tau}) \middle| \mathcal{F}_t \right\}, \qquad (2)$$

where β is an additional discount factor, which represents present bias model (2) will be reduced to model (1) when $\beta = 1$.

However, in the financial markets, the yield curve (of riskless assets) is typically upward sloping, and we observe an *inverted* yield curve only during liquidity crises or at times of financial distress. Thus, there appears to be a discrepancy between the results of laboratory experiments or field surveys and the market data. One possible explanation for the discrepancy is that liquidity or credit constraints may affect time discount rates. Among existing empirical studies based on micro data, Pender (1996) examined the impacts of credit constraints on discount rates, and found that credit constrained people tend to have higher discount rates. Thus, the discount rates revealed by laboratory experiments or field surveys may not be directly representing time preference, but are affected by the environment too.

This paper examines the impacts of the environment on time preference empirically, such as credit constraints, uncertainties surrounding the agent,

[3] See for instance Gilboa and Marinacci (2013) for a survey on the literature.
[4] See for instance Frederick, *et al*. (2002) for a literature review.

past loss experience, education level and wealth (income, asset). In particular, we first regress subjective interest rates on these variables, and see if the often observed inverted yield curve from experiments can be explained as a result of these factors. We then test the discounted expected utility model with possible quasi-hyperbolic discounting (2). If model (2) is the correct model, the two parameters β and ρ are primitives that represent the agent's preferences, and they will not be affected by the environment. However, if they are functions of environmental variables such as past loss experience, they are not genuine primitives, and the representation of preferences requires more structure than provided in the discounted expected utility model (2).

The remainder of the paper proceeds as follows. Section 2 explains the data and the econometric models we use for the empirical analyses. The econometric models include model (2) with and without credit constraints as well as reduced-form models of subjective interest rates. Section 3 reports the estimation results and their implications. In particular, we discuss if the null hypothesis that parameters β and ρ are genuine primitives is rejected or not. Finally, Section 4 concludes the paper.

2. Data and Econometric Models

In this section, we first describe the data we use for the empirical analyses. We then present the econometric models that test the null hypothesis that the discounted expected utility model (2) represents the preferences of agents, with an emphasis on the appropriateness of the two parameters β and ρ as genuine primitives of the representation.

2.1. Data

We utilise a unique survey data set jointly collected in Viet Nam by the Research Institute of Economy, Trade and Industry (RIETI) of Japan and Viet Nam's Center for Agricultural Policy from late February 2008 until April 2008, which we call the RIETI-CAP survey. Since the RIETI-CAP survey aims at collecting data to facilitate the design of an insurance scheme against avian influenza (AI) and flooding, sub-samples of VHLSS (Viet

Nam Household Living Standards Survey) 2006 were chosen from four provinces: (1) Ha Tay (hit only by AI); (2) Nghe An (hit only by flooding); (3) Quang Nam (hit both by AI and flooding); and (4) Lao Cai (hit neither by AI nor by flooding). The selection of these four provinces was made using commune questionnaire data in VHLSS 2004.[5] Table 5.1 reports the average numbers of natural disasters and animal epidemics per commune for the five years to 2004 in the above four provinces.

Table 5.1: The Average Numbers of Natural Disasters and Epidemics per Commune in the Five Years to 2004

Province	Floods	Typhoons	Droughts	Natural disasters	Epidemics
Ha Tay	0.042	0.042	0.000	0.083	*0.917*
Lao Cai	0.111	0.333	0.000	0.444	0.333
Nghe An	*0.533*	0.111	0.378	*1.022*	0.444
Quang Nam	*0.500*	0.143	0.393	*1.036*	*0.714*
Nationwide	0.375	0.292	0.235	0.902	0.656

Data: VHLSS 2004.

The households covered in the REITI-CAP data include both those with and without the expenditure module in VHLSS 2006. The data cover approximately 500 households from each province, of which 100 households are with both income and expenditures data and 400 households with income data only. The data set contains extensive information, such as current and retrospective income and expenditure information, asset information, insurance subscriptions, borrowings, past loss experiences of natural disasters in the last five years, subjective probability assessments of AI and/or flooding, the maximum willingness-to-pay for various hypothetical insurance schemes, and subjective interest rates. Table 5.2 reports the summary statistics and the distributions of past loss experiences. It is clear from the table that no household experienced AI losses more than three times, while some households incurred losses from floods more than three times in the last five years.

Regarding subjective interest rates, the RIETI-CAP survey asks the following questions:

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[5] Viet Nam's administrative division system (for rural areas) has the following hierarchy; (top to bottom) provinces – districts – communes.

Willingness-to-pay question for loans: *Imagine that you have an opportunity to receive a loan from a local non-governmental organisation. Please tell us the maximum amount you would be willing to pay back for each a loan of VND 100,000 (Vietnamese dong); VND 1, 000, 000; and VND 4, 000, 000 after one day, after three months and after one year.*

Table 5.2: Past loss experience of households in the last five years

Causes of losses	Number of loss experiences							Total	Mean	Std dev
	0	1	2	3	4	5	6			
AI	1827	161	26	4	0	0	0	2018	0.1115	0.3699
Flood	1553	356	83	20	4	2	0	2018	0.3013	0.6293
Typhoon	1575	401	35	7	0	0	0	2018	0.2438	0.4899
Drought	1903	97	4	14	0	0	0	2018	0.0728	0.3364
Hail	1963	51	3	1	0	0	0	2018	0.0297	0.1866
Landslide	2001	14	3	0	0	0	0	2018	0.0099	0.1131
Other epidemics	1557	306	83	20	17	34	1	2018	0.3845	0.9120
Other disasters	1732	218	52	14	2	0	0	2018	0.1843	0.5055

Data: The RIETI-CAP survey.

Thus, the questions are in fact willingness-to-pay questions, and we can deduce the subjective interest rates based on the responses. Let $W^h_{P,t}$ denote respondent *h*'s willingness-to-pay for a loan with principal *P* and time-to-maturity *t*. Then, respondent *h*'s subjective interest rate $r^h_{P,t}$ will be defined as follows when we use continuous compounding:

$$r^h_{P,t} := \frac{1}{t} \ln \frac{W^h_{P,t}}{P}.$$

Figure 5.1: Average Subjective Interest Rates (annualised)

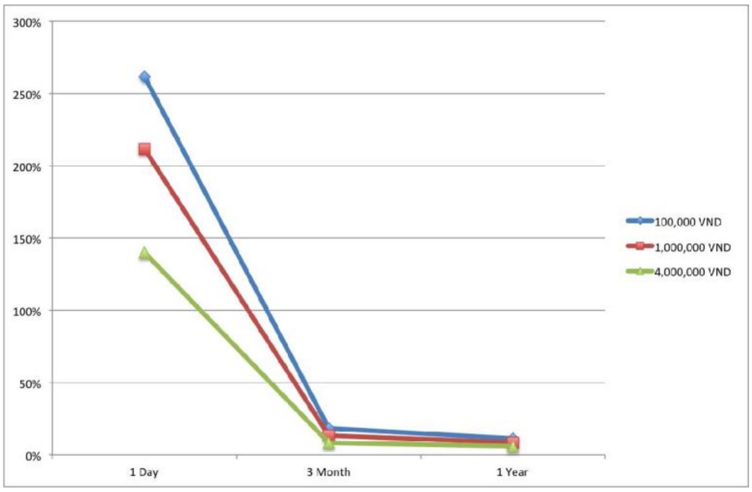

Figure 5.1 shows the cross-sectional average subjective interest rates for loans with different principals and time-to-maturity, i.e, $\bar{r}_{P,t} := \frac{1}{H}\sum_{h=1}^{H} r_{P,t}^{h}$, where H is the number of samples (households). It indicates that the subjective interest rate is on average decreasing in time-to-maturity t; thus, the yield curves are inverted. Also, the subjective interest rate is decreasing in the amount of loan principal P, which implies that the Law of One Price is violated—the Law of One Price requires $r_{P,t}^{h}$ (or $\bar{r}_{P,t}$) to be independent of P. These two aspects are consistent with numerous existing results based on similar questionnaires, as noted above. However, they are incompatible with the shape of the yield curve usually found in the financial markets, which is upward sloping, except during liquidity crises. This suggests that the subjective interest rates may be affected by binding credit/liquidity constraints, arising for various reasons such as chronic poverty and a severe loss suffered in the recent past.

Regarding borrowing and/or credit constraints, the RIETI-CAP survey asks the following series of questions:

Question 1: *Did your household borrow money? Please answer separately for 2006 and 2007. Please consider all the different sources such as government agency, agricultural development bank, commercial banks, credit unions, cooperatives, non-governmental organisations, you prefer to the other by circling (a) or (b) for each pair below micro-finance, pawn shops, ROSCA (Choi Ho/Hui), landlord, employer, relatives, friends, and* *other sources.* YES [Go to Question 2]; NO [Go to Question 3].

Question 2: *Could your household borrow as much as you wanted (needed)?* YES/NO. [END]

Question 3: *What is the primary reason why you did not borrow money?*
1. No need; 2. Applied but rejected; 3. Believed would be rejected; 4. Too expensive; 5. Inadequate collateral; 6. Do not like to be indebted; 7. Fearful of default; 8. Others [Specify]. [Proceed to Question 4]

Question 4: *Please indicate any other reasons why you did not borrow money. Please select any applicable reasons.*
1. No need; 2. Applied but rejected; 3. Believed would be rejected; 4. Too expensive; 5. Inadequate collateral; 6. Do not like to be indebted; 7. Fearful of default; 8. Others [Specify].

From the above series of questions, we generate several dummy variables. To do so, we first make the following distinction:

- Not Credit Constrained: If answered 'Yes' to both Questions 1 and 2; or if answered 'No' to Question 1 and '1' to Question 3;
- Credit Constrained: All other households.

Since we asked the same set of questions for 2006 and 2007, these definitions enable us to generate dummy variables including: *Credit constrained only in 2006*, *Credit constrained only in 2007* and *Credit constrained both in 2006 and in 2007*.

Furthermore, the RIETI-CAP survey asks the following questions on attitude towards risk:

Questions on attitude towards risk: *Imagine a fair coin flip. Choose the option that you prefer to the other by circling (a) or (b) for each pair below*

By combining answers to **4-1** and **4-2**, we may categorise the respondents into the following three types:

$$\textbf{4-1} \begin{cases} (a) & \textit{Whatever the outcome (Heads or Tails), you receive 30,000 VND.} \\ (b) & \textit{You receive 60,000 VND if Heads, and nothing otherwise.} \end{cases}$$

$$\textbf{4-2} \begin{cases} (a) & \textit{Whatever the outcome (Heads or Tails), you receive 30,000 VND.} \\ (b) & \textit{You receive 75,000 VND if Heads, and nothing otherwise.} \end{cases}$$

$$\textbf{4-3} \begin{cases} (a) & \textit{Whatever the outcome (Heads or Tails), you lose 30,000 VND.} \\ (b) & \textit{You lose 60,000 VND if Heads, and nothing otherwise.} \end{cases}$$

By combining answers to 4-1 and 4-2, we may categorise the respondents into the following three types:

(1) *Highly risk averse* if (a) was chosen for both **4-1** and **4-2**;
(2) *Moderately risk averse* if (a) was chosen for **4-1** and (b) for **4-2**;
(3) *Risk loving 1* if (b) was chosen for both **4-1** and **4-2**.

We disregard respondents who chose (b) for **4-1** and (a) for **4-2**, because such a combination violates monotonicity. Moreover, we may categorise the respondents into the following three types by combining answers to **4-1** and **4-3**:

(1) *Risk averse* if (a) was chosen for both **4-1** and **4-3**;
(2) *Loss averse* if (a) was chosen for **4-1** and (b) for **4-3**;
(3) *Risk loving 2* if (b) was chosen for both **4-1** and **4-3**.

Although it is possible that one may choose (b) for **4-1** and (a) for **4-3**, we disregard such a combination, because it is a perverse case.

2.2. Econometric Models

We first estimate the following reduced-form linear regression model of subjective interest rates:

$$r^h_{P,t} = X^h \alpha_{P,t} + \varepsilon^h_{P,t}, \tag{3}$$

where X^h is a set of control variables such as credit constraints, dummies and loss experience variables and $\varepsilon^h_{P,t}$ is the random error term. The estimation results would indicate what determines the shape of subjective yield curves.

For instance, if credit/liquidity constraints are active for respondent *h*'s household, then *h*'s subjective short-term interest rate would be higher.

Now, we assume that the preferences of the respondents have a discounted expected utility representation with a power utility, i.e.,

$$u^h(x) = \frac{x^{1-\gamma^h}}{1-\gamma^h}.$$

Then, we estimate two parameters *β* and *p* in the following Euler equation by generalised method of moments (GMM): For every loan with principal *P* and time to maturity *t*, and for every respondent/household *h*,

$$P^{-\gamma^h} = \beta \cdot \left(\frac{1}{1+\rho}\right)^t E^h \left\{ R^h_{P,t} \cdot \left(W^h_{P,t}\right)^{-\gamma^h} \middle| \mathcal{F}^h \right\}, \tag{4}$$

where γ^h is respondent *h*'s coefficient of relative risk aversion, E^h is respondent *h*'s expectation operator, F^h is *h*'s current information set (a *σ*-algebra) and $R^h_{P,t} := W^h_{P,t}/P$.[6][7]

Moreover, to see if the parameters *β* and *p* are affected by exogenous factors, we estimate model (4) with an additional structure for *β* and *p* so that they may be different across households as follows:

$$\begin{aligned} \beta^h &= \beta_0 + X^h\beta_1 + \epsilon^h; \\ \rho^h &= \rho_0 + X^h\rho_1 + \nu^h. \end{aligned}$$

Also, to reflect the impacts of possible credit constraints, we estimate the following Euler equation by GMM: For every loan with principal *P* and time to maturity *t*, and for every respondent/household *h*,

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[6] To simplify notation, no time index such as *Γ* with $F^h{}_\tau$ is given, since we are not explicitly analysing the dynamical behaviour of economic variables in the paper.

[7] Since $W^h{}_{P,t}$ itself is riskless, it appears that there is no need to form a conditional expectation here. However, we are representing the future consumption, which is essentially random, with $W^h{}_{P,t}$ by convenience; thus, we use GMM with instruments to assure orthogonality conditions to be satisfied.

$$P^{-\gamma^h} = \beta \cdot \left(\frac{1}{1+\rho}\right)^t E^h \left\{ R^h_{P,t} \cdot (W^h_{P,t})^{-\gamma^h} \middle| \mathcal{F}^h \right\} + \sum_{z \in Z^h} \lambda^h_z, \qquad (5)$$

where $\lambda^h{}_z$ (> 0) is the Lagrange multiplier(s) for a credit constraint represented by variable z and Z^h is a set of variables representing credit constraints.

Let $\hat{\beta}$ and $\hat{\rho}$ denote the estimates of β and ρ in model (5), respectively. Also let $\hat{\beta}_o$ and $\hat{\rho}_o$ donate the estimates of β and ρ in model (4). If the credit constraints, and they will be biased due to the omission of active credit constraints: $\hat{\beta}_o > \hat{\beta}$ and $\hat{\rho}_o > \hat{\rho}$. It follows that the estimates $\hat{\beta}_o$ and $\hat{\rho}_o$ would tend to indicate a lower present bias (a larger estimate of β) and a lower discount rate (a smaller estimate of ρ).

To estimate β and ρ, we fix respondent *h*'s coefficient of relative risk aversion γ^h by referring to the answers to the questions on attitude towards risk above. More specifically, by assuming a power utility we can deduce the range of γ^h for the three types as follows: for respondents who are *highly risk averse* $\gamma^h \geq 0.24$; for respondents who are *moderately risk averse* $\gamma^h \in (0, 0.24)$; and for respondents who are *risk loving* $\gamma^h \leq 0$. It is however not very straightforward how we should fix γ^h for each of these three ranges. Thus, we fix γ^h in three different ways as reported in Table 5.3. The column labelled 'Simple' sets $\gamma^h = 0$ for risk loving respondents, $\gamma^h = 0.12$ for moderately risk averse respondents, and $\gamma^h = 0.24$ for highly risk averse respondents. The column labelled 'Tanaka' refers to Tanaka, *et al*. (2010), and the three values are the mean values of γ for people in the corresponding three ranges of γ from the data used in Tanaka et al. (2010). Finally, the column labeled 'Fitted' refers to fitted values of interval regression model (4) reported in Table B.1 in the Appendix. We use the fixed values of γ^h specified in Table 5.3.

Table 5.3: Fixed Values of the Relative Risk Aversion Parameter γ^h

Types	Simple	Tanaka	Fitted	Households	Share
Risk loving	0	0.05	[0, 0.001)	345	21.88%
Moderately risk	0.12	0.097	[0.001, 0.24)	225	14.27%
Highly risk averse	0.24	0.6765	[0.24, +oc)	1007	63.86%
Total				1,828	100%

3. Estimation Results

In this section, we present and examine the estimation results of the econometric models described in the previous section. The estimation results of the reduced-form regression model (3) are reported first, followed by the estimation results of Euler equations (4) and (5).

3.1. Reduced-form regressions of subjective interest rates

All estimation results of the reduced-form regression model (3) are presented in section C in the Appendix. Table C.1 shows the results of regressions of subjective interest rates on various attributes of the respondents. The province dummy variables *Ha Tay*, and in particular, *Quang Nam* are statistically significant and have positive point estimates for regressions of overnight interest rates. Recall that Quang Nam was frequently hit both by avian influenza and by floods—the province is prone to disasters or epidemics. Thus, it may be the case that frequent natural disasters and/or epidemics are negatively affecting the livelihood of the residents, and credit constraints may be tighter in Quang Nam.

The results of regressions on subjectively perceived credit constraints are shown in Table C.2. Clearly they do not support the hypothesis that credit constraints raise short-term subjective interest rates than long-term subjective interest rates, contrary to what we often observe in the financial market during liquidity crises for market interest rates. However, the credit constraint variables used in the estimations here are constructed from questions that ask the perception of the respondent towards the borrowing possibilities, and the respondents are not necessarily credit constrained even if they perceive as such.

Table C.3 reports the results of regressions on past loss experiences caused by various disasters. *Flood* along with *Typhoon* are statistically significant and have positive point estimates for regressions of overnight interest rates. *AI* and *Other epidemics* are also statistically significant for many regressions, but their point estimates for overnight interest rates regressions are not as large as those of *Flood* or *Typhoon*. Also, we see from Table C.4 that the number of past loss experiences of both AI and floods is statistically significant for overnight interest rates regressions, although the point estimates are higher for floods. These suggest that flood losses may have strong impacts on the subjective overnight interest rates, possibly due to tighter credit constraints. Table C.5, meanwhile, reports the estimation results of regressions on various natures of losses/damages, and *house damage* has a markedly high point estimate for overnight interest rates regressions.

Regressions on attitude towards risk and those on loss aversion types are reported in Tables C.6 and C.7, respectively. The highly risk averse type in Table C.6 and the risk averse type is Table C.7 are treated as the baseline case. For a loan principal of VND 100,000 ('100' in the tables), risk loving types in both tables exhibit higher subjective interest rates than other types, for overnight rates in particular. However, there is no obvious pattern for a larger loan principal.

Finally, the effects of change in income are displayed in Table C.8. An increase in income is associated with a lower subjective interest rates especially for overnight rates, except when the loan principal is VND 100,000 ('100' in the table). The result is consistent with the hypothesis that active credit constraints raise the subjective interest rates.

3.2. Estimation Results of the Euler Equations

We first estimate model (4) with no constraints by CMM. In so doing, we use the following instruments: *asset*, *age*, *age_sq*, *education level of the household head*, *education level of the household head's spouse* and *household size*, and *number of disaster-type experienced from 2003 to 2006*, with disaster-type here refering to AI, flood, typhoon, drought, hail, landslide and other epidemics.[8] Table D.1 reports the estimation results of ρ when β is fixed at β = 0.99, while Table D.2 shows the estimates of β with ρ fixed at ρ = 0.0002. Note that we measure the time to maturity t in terms of days here: t = 1 for one day, t = 31 for one month and t = 365 for one year. Thus, the discount rate ρ is a daily rate, and ρ = 0.0002 corresponds approximately to an annual rate of 7.57%. The results of these two tables indicate that the estimates of β and ρ are compatible at around (β, ρ) = (0.99, 0.0002) for all three specifications of γ, the coefficient of relative risk aversion.[9] We therefore set, either β = 0.99 or ρ = 0.0002 in all other estimations of models (D.1) and (D.2).

Table D.3 reports the estimates of ρ with β fixed at β= 0.99 when *CCin2007*, a subjective credit constraints in 2007, is included in models (4) and (5). The first three columns are estimates of model (4), and it is clear that *CCin2007* is statistically significant and is positive. Hence, respondents who are subjectively credit constrained in 2007 tend to have a higher subjective discount rate ρ. Columns (4)—(6) are estimates of model (5). While *CCin2007* itself is insignificant, the interaction terms between *CCin2007* and *asset* and between *CCin2007* and *income* are significant in most cases, where the former tends to be positive and the latter negative. Thus, it appears that a larger possession of assets is associated with a tighter credit constraint while a higher income is associated with a looser credit constraint, indicating that we need to be aware of the distinction between stock and flow, although it is not straightforward how to interpret the positive sign for the interaction term between *CCin2007* and *asset*. Columns (7)—(9) show that *CCin2007* has a positive impact on ρ, while a negative λ is in conflict with model (5), which requires the shadow price of a credit constraint λ to be positive. Meanwhile, Table D.4 reports estimates of β for the corresponding cases, and the implications are the same as the ones from Table D.3.

Next, Table D.5 shows the estimates of ρ when past experiences of AI and floods are included in models (4) and (5). Both AI and floods are

[8] In the list of variables in the Appendix, they are No. of cases of AI 2003—2006, No. of floods 2003—2006, No. of typhoons 2003—2006, No. of droughts 2003—2006, No. of hail storms 2003—2006, No. of landslides 2003—2006 and No. of epidemics 2003—2006.
[9] Ideally, both 0 and p should be estimated simultaneously. However, we have so far failed to achieve a reliable converge

significantly positive in columns (1)—(3), suggesting that disaster experience is positively correlated with discount rate ρ. Columns (4)—(6) meanwhile suggest that both asset and income have opposing impacts between AI and floods for the interaction terms. Although these opposing impacts for the interaction terms remain the same for columns (7)—(9), both AI and floods are no longer significant for ρ itself for columns (7) and (8). One possible interpretation of the opposing impacts of asset and income between AI and floods for the interaction terms is that flood losses mainly concern assets and AI losses concern income, although the positive signs for the interaction terms are hard to interpret. Table D.6 reports the corresponding estimates of β, and the results are essentially the same as those of Table D.5.

The estimates of ρ when the nature of past losses is included in models (4) and (5) are presented in Table D.7. Both house damage and physical livestock loss dummy variables have a significant impact on ρ in columns (1)-(3), indicating that damage or loss incurred to asset (stock) is positively correlated with discount rate ρ. Also, columns (4)-(6) reveal that both house damage and physical livestock loss has a positive sign, consistent with the hypothesis that severe losses tighten the credit constraints, which result in higher subjective interest rates. The interaction term between physical livestock loss dummy and asset has a negative sign in columns (4)-(6), which implies that among households who incurred physical livestock loss, a larger asset holding helps relieve the credit constraints. However, the interaction term between harvest loss dummy and asset has a positive sign, which, perversely, suggests that, among households who incurred harvest losses, households with a larger asset holding face a tighter credit constraint. But the results reported in columns (7)-(9) show that the effects presented in columns (1)-(3) and those in columns (4)-(6) cancel each other out, and almost no variable remains statistically significant. The results presented in Table D.8 are by and large the same as those of Table D.7. However, the results shown in columns (7)-(9) are slightly different between the two tables. In Table D.8, harvest loss has a negative effect on β which indicates more impatience among households who incurred harvest losses, while the opposite holds for households who incurred physical livestock losses. However, the comparisons between columns (1)-(3) and (7)-(9) in both Tables D.7 and D.8 reveal that the estimates of ρ are higher in (1)-(3) than in (7)-(9) and those of β are lower for (1)-(3) than in (7)-(9), contrary to the estimation bias anticipated.

This suggests that the model specification is not appropriate.

4. Conclusion

In this paper, we examined the impacts of the environment, subjectively perceived credit constraints and loss experiences in the recent past in particular, on subjective interest rates as well as on time preference by using the household data of the RIETICAP survey. The reduced form linear regressions of the subjective interest rates revealed that flood loss experience as well as house damage and physical livestock losses have a large impact, especially on overnight interest rates, although subjectively perceived credit constraints have only negligible impacts. Moreover, households in Quang Nam province, who tend to be prone to both AI and floods, indicated particularly high subjective interest rates, the overnight interest rate in particular. Thus, it appears that losses or damage caused by floods on physical assets such as houses or livestock would make the financial situation of the affected households very tight, which is reflected in the high subjective interest rates, especially the overnight rates. Moreover, changes in income tend to have an impact on the subjective interest rates, lower rates when the household's income has increased, which is consistent with the hypothesis that active credit constraints raise subjective interest rates.

Furthermore, we tested the discounted expected utility framework that admits quasi-hyperbolic discounting with a power utility as in the von Neumann-Morgenstern utility. The estimation results show that the present bias is not very substantial, yet statistically significant. Moreover, estimations that allow for the presence of active credit constraints show that subjectively perceived credit constraints have no impact in general. However, households who subjectively perceive themselves to be credit constrained tend to have a higher time discount, and the same applies for households who incurred losses from AI and/or floods. Nevertheless, the impacts of AI or flood loss experience on time preference parameters are not robust when we take into account the impacts of the losses through credit constraints. Moreover, the estimations of the effects of credit constraints are rather hard to interpret. On one hand, the credit constraints tend to be tighter for households with a larger asset holding among those who experienced AI losses, while the opposite is true for households who experienced flood losses. On the other hand, the constraints tend to be looser for households with a higher income holding among those who experienced AI losses, and again the opposite is true for households who experienced flood losses. This may well be reflecting possible issues with the specification of the model itself, since the estimation model assumes a very restrictive representation of preferences—in particular, time preference is represented by two parameters and risk attitude by a single parameter.

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A List of Variables and Summary Statistics

List of Variables

Respondent characteristics
rural: dummy, 1 if the household is living in a rural area;
wife: dummy, 1 if the respondent is the household head's wife;
husband: dummy, 1 if the respondent is the household head's husband;
son: dummy, 1 if the respondent is the household head's son;
daughter: dummy, 1 if the respondent is the household head's daughter;
others: dummy, 1 if the respondent is not the household head's spouse or child;
age: the age of the household head;
Ha Tay: province dummy, 1 if Ha Tay;
Lao Cai: province dummy, 1 if Lao Cai;
Nghe An: province dummy, 1 if Nghe An;
Quang Nam: province dummy, 1 if Quang Nam;
household size: the number of household members.

Education level
HH no degree: dummy, 1 if household head (HH) has no degree;
HH primary school: dummy, 1 if HH's highest degree is primary school;
HH lower secondary school: dummy, 1 if HH's highest degree is lower secondary school; *HH upper secondary school*: dummy, 1 if HH's highest degree is upper secondary school; *HH junior college*: dummy, 1 if HH's highest degree is junior college;
HH tertiary: dummy, 1 if HH's highest degree is tertiary;
HH education no info: dummy, 1 if no info about HH's highest degree;
Spouse no degree: dummy, 1 if HH spouse has no degree;
Spouse primary school: dummy, 1 if HH spouse's highest degree is primary school;
Spouse lower secondary school: dummy, 1 if HH spouse's highest degree is lower secondary school; *Spouse upper secondary school*: dummy, 1 if HH spouse's highest degree is upper secondary school; *Spouse junior college* : dummy, 1 if HH spouse's highest degree is junior college;
Spouse tertiary: dummy, 1 if HH spouse's highest degree is tertiary;
Spouse other education: dummy, 1 if HH spouse's highest degree is other education; *Spouse education no info*: dummy, 1 if no info about HH spouse's highest degree.

Credit constraint
CC in 2006: dummy, 1 if credit constrained in 2006;
CC in 2007: dummy, 1 if credit constrained in 2007;
Not CC: dummy, 1 if not credit constrained in 2006 and in 2007;
CC only in 2006: dummy, 1 if *CC in 2006* = 1 and *CC in 2007* = 0;
CC only in 2007: dummy, 1 if *CC in 2006* = 0 and *CC in 2007* = 1;
CC both in 2006 and 2007: dummy, 1 if *CC in 2006* = 1 and *CC in 2007* = 1.

Past loss experience
No. of loss experiences: no. of times of losses experienced in the last five years; *AI*: dummy, 1 if the household incurred AI losses in the last five years;
flood: dummy, 1 if the household incurred flood losses in the last five years; *typhoon*: dummy, 1 if the household incurred typhoon losses in the last five years; *drought*: dummy, 1 if the household incurred drought losses in the last five years; *hail*: dummy, 1 if the household incurred hail losses in the last five years;
landslide: dummy, 1 if the household incurred landslide losses in the last five years;
other epidemics: dummy, 1 if the household incurred losses from epidemics (except AI) in the last five years;
No. of AI: number of AI experienced in the last five years;
No. of floods: number of floods experienced in the last five years;
No. of AI 2003—2006: number of AI experienced from 2003 to 2006;
No. of floods 2003—2006: number of floods experienced from 2003 to 2006;
No. of typhoons 2003—2006: number of typhoons experienced from 2003 to 2006; *No. of droughts 2003—2006*: number of droughts experienced from 2003 to 2006; *No. of hails 2003—2006*: number of hails experienced from 2003 to 2006;
No. of landslides 2003—2006: number of landslides experienced from 2003 to 2006;
No. of epidemics 2003—2006: number of epidemics (excluding AI) experienced from 2003 to 2006.

Nature of past losses/damages
house lost: dummy, 1 if house was lost;
house damage: dummy, 1 if house was damaged;
physical assets loss: dummy, 1 if losses of physical assets;
physical livestock loss: dummy, 1 if livestock lost physically;

economic livestock loss: dummy, 1 if economic losses of livestock incurred;
harvest loss: dummy, 1 if harvest was lost;
human casualty: dummy,1 if human casualty suffered;
human sickness/injury: dummy, 1 if human sickness/injury suffered;
other losses: dummy, 1 if losses of other nature incurred.

Attitude towards risk (See Section 2 for details)
highly risk averse: dummy;
moderately risk averse:
dummy; *risk loving 1*:
dummy;
risk averse: dummy;
loss averse: dummy;
risk loving 2: dummy.

Assets
asset: total value of assets;
livestock: total value of
livestocks.

Income
income: annual income in 2007 (in thousand VND);
change in income: index variable categorised according to the change in income in the last year.

Table A.1: Descriptive statistics

	Count	Mean	SD	Min	Max
Respondent characteristics					
rural*	1583	0.91	0.29	0	1
wife*	1583	0.19	0.4	0	1
husband*	1583	0.02	0.12	0	1
son*	1583	0.03	0.17	0	1
daughter*	1583	0.01	0.11	0	1
others*	1583	0.03	0.18	0	1
Age	1583	50.9	14.21	20	96
Lao Cai*	1583	0.24	0.42	0	1
Nghe An*	1583	0.26	0.44	0	1
Quang Nam*	1583	0.25	0.43	0	1
household size	1583	4.18	1.75	1	14
Education Level					
HH no degree*	1583	0.01	0.08	0	1
HH primary school*	1583	0.28	0.45	0	1
HH lower secondary school*	1583	0.31	0.46	0	1
HH upper secondary school*	1583	0.11	0.31	0	1
HH junior college*	1583	0.0038	0.06	0	1
HH tertiary*	1583	0.01	0.11	0	1
HH education no info*	1583	0.28	0.45	0	1
Spouse no degree*	1583	0.0044	0.07	0	1
Spouse primary school*	1583	0.21	0.4	0	1
Spouse lower secondary school*	1583	0.26	0.44	0	1
Spouse upper secondary school*	1583	0.06	0.24	0	1
Spouse junior college*	1583	0.01	0.1	0	1
Spouse tertiary*	1583	0.01	0.09	0	1
Spouse other education*	1583	0.0006	0.03	0	1
Spouse education no info*	1583	0.45	0.5	0	1
Credit constraint					
CC in 2006*	1583	0.35	0.48	0	1
CC in 2007*	1583	0.37	0.48	0	1
Not CC*	1583	0.58	0.49	0	1
CC only in 2006*	1583	0.05	0.21	0	1
CC only in 2007*	1583	0.07	0.26	0	1
CC both in 2006 and in 2007*	1583	0.3	0.46	0	1
Past loss experience					
No. of loss experiences	1583	1.36	1.37	0	8
AI*	1583	0.09	0.29	0	1
flood*	1583	0.22	0.42	0	1
typhoon*	1583	0.22	0.41	0	1
drought*	1583	0.06	0.23	0	1
hail*	1583	0.03	0.16	0	1
landslide*	1583	0.01	0.08	0	1
other epidemics*	1583	0.24	0.43	0	1
No. AI	1583	0.11	0.37	0	3
No. floods	1583	0.29	0.63	0	5

No. of AI 2003—2006	1583	0.07	0.28	0	3
No. of floods 2003—2006	1583	0.08	0.33	0	4
No. of typhoons 2003—2006	1583	0.16	0.39	0	2
No. of droughts 2003—2006	1583	0.03	0.17	0	1
No. of hails 2003—2006	1583	0.01	0.11	0	2
No. of landslides 2003—2006	1583	0.0038	0.07	0	2
No. of epidemics 2003—2006	1583	0.28	0.76	0	4
Nature of past losses/damages house lost*	1583	0.0025	0.05	0	1
house damage*	1583	0.13	0.34	0	1
physical assets loss*	1583	0.07	0.26	0	1
physical livestock loss*	1583	0.28	0.45	0	1
economic livestock loss*	1583	0.06	0.23	0	1
harvest loss*	1583	0.4	0.49	0	1
human casualty*	1583	0.0038	0.06	0	1
human sickness/injury*	1583	0.01	0.09	0	1
other losses*	1583	0.01	0.12	0	1
Attitude towards risk highly risk averse*	1577	0.64	0.48	0	1
moderately risk averse*	1577	0.14	0.35	0	1
risk loving 1*	1577	0.22	0.41	0	1
risk averse*	1576	0.43	0.49	0	1
loss averse*	1576	0.36	0.48	0	1
risk loving 2*	1576	0.22	0.41	0	1
Assets asset (thousand VND):	1583	2054.48	4062.67	0	18650
livestock (thousand VND):	1583	275.26	1345.73	0	15000
Income income	1583	21903.72	14332.14	661.5	74280
change in income	1583	1.11	0.11	0.6	1.75

* Dummy variables.

B. Interval Regressions of *γ*

Table B.1. Interval Regressions of *γ*

	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
HH head Primary	-	-0.201*	-0.210*	-0.220*	asset			-0.0293*	-0.0275
	(0.	(0.117)	(0.119)	(0.118)				(0.0174)	(0.0174)
HH head Lower	-	-0.185	-0.194	-0.202*	livesto			-0.0446	-0.0484
	(0.	(0.118)	(0.120)	(0.118)				(0.0504)	(0.0506)
HH head Upper	-	-0.171	-0.181	-0.192	AI				-0.0219
	(0.	(0.119)	(0.121)	(0.120)					(0.0228)
HH head Junior	-	-0.218	-0.231	-0.237	flood				-0.0298
	(0.	(0.156)	(0.158)	(0.156)					(0.0184)
HH head Bachelor	-	-0.228*	-0.233*	-0.237*	typhoo				0.000183
	(0.	(0.133)	(0.134)	(0.133)					(0.0184)
HH head Education	-	-0.212*	-0.221*	-0.233**	drough				0.0443
	(0.	(0.117)	(0.119)	(0.117)					(0.0315)
HH Spouse Primary	-	-0.120	-0.116	-0.129	hail				0.0816*
	(0.	(0.110)	(0.110)	(0.110)					(0.0448)
HH Spouse Lower	-	-0.0831	-0.0786	-0.0905	landsli				0.0327
	(0.	(0.110)	(0.110)	(0.110)					(0.0850)
HH Spouse Upper	-	-0.0897	-0.0880	-0.0951	other				0.00458
	(0.	(0.113)	(0.113)	(0.113)					(0.0166)
HH Spouse Junior	-	-0.147	-0.146	-0.158	other				- [illegible]
	(0.	(0.126)	(0.127)	(0.126)					(0.0194)
HH Spouse Master	-	-0.106	-0.109	-0.112	consta	0.530***	0.597***	0.610***	0.632***
	(0.	(0.135)	(0.135)	(0.135)	(0.151)	(0.148)	(0.150)	(0.150)	
HH Spouse Other	-	-0.255	-0.256	-0.351					
	(0.	(0.259)	(0.259)	(0.261)					
HH Spouse Education	-	-0.0423	-0.0403	-0.0526					
	(0.	(0.109)	(0.110)	(0.110)					
Ha Tay		-0.0502**	-0.0523***	-0.0502**					
		(0.0199)	(0.0200)	(0.0208)					
Nghe An		0.0601***	0.0631***	0.0756***					
		(0.0213)	(0.0213)	(0.0228)					
Quang Nam		-0.0906***	-0.0918***	-0.0760***					
		(0.0193)	(0.0193)	(0.0224)					
ln(sigma) constant						-	-	-	-
						(0.0352)	(0.0351)	(0.0351)	(0.0351)
Observations						1577	1577	1577	1577

The numbers in parentheses are standard errors. * $p < .10$, ** $p < .05$, *** $p < .01$ The unit of fixed asset and livestock is set at million VND.

C Estimation results of reduced-form regressions of subjective interest rates

Table C.1: Regressions on respondent's attributes

	100 D	100 M	100 Y	1000 D	1000 M	1000 Y	4000 D	4000 M	4000 Y
rural	-3.087***	-0.0163	-0.00416	-1.205***	0.0219	0.0156**	0.350	0.0262***	0.0177***
	(0.567)	(0.0188)	(0.00979)	(0.396)	(0.0138)	(0.00680)	(0.232)	(0.00667)	(0.00418)
wife	0.753*	0.0593***	0.0207***	0.555*	0.0117	0.00178	0.211	-0.000286	-0.0000828
	(0.406)	(0.0135)	(0.00699)	(0.283)	(0.00989)	(0.00485)	(0.166)	(0.00476)	(0.00298)
husband	-1.257	-0.0273	-0.00480	-0.221	-0.00154	0.00510	-0.0132	0.0350**	0.0236**
	(1.278)	(0.0425)	(0.0221)	(0.893)	(0.0312)	(0.0153)	(0.523)	(0.0150)	(0.00941)
son	-0.273	0.0347	0.0210	-0.278	0.00358	0.00128	-0.0985	0.00260	0.00123
	(0.896)	(0.0298)	(0.0155)	(0.626)	(0.0219)	(0.0107)	(0.367)	(0.0105)	(0.00660)
daughter	-1.710	0.0133	0.00118	-2.005**	0.0309	0.0271	-0.970*	0.0144	0.0158
	(1.397)	(0.0464)	(0.0241)	(0.976)	(0.0341)	(0.0167)	(0.572)	(0.0164)	(0.0103)
others	-0.315	-0.00184	-0.00207	0.253	0.0323	-0.00423	0.446	0.00767	-0.00487
	(0.882)	(0.0293)	(0.0152)	(0.616)	(0.0215)	(0.0106)	(0.361)	(0.0104)	(0.00650)
Age	0.0264	0.000178	0.00162	-0.0534	-0.000965	-0.000173	0.0167	0.000931	0.000549
	(0.0747)	(0.00247)	(0.00128)	(0.0522)	(0.00182)	(0.000891)	(0.0306)	(0.000875)	(0.000547)
age sq	-0.000419	-0.00000505	-0.0000192*	0.000479	0.00000190	-0.00000222	-0.000215	-0.0000121	-0.00000733
	(0.000677)	(0.0000224)	(0.0000116)	(0.000473)	(0.0000165)	(0.00000808)	(0.000277)	(0.00000792)	(0.00000496)
Ha Tay	1.121**	-0.0873***	-0.0284***	0.837***	0.0271**	0.0345***	0.221	0.0292***	0.0330***
	(0.460)	(0.0153)	(0.00791)	(0.321)	(0.0112)	(0.00550)	(0.188)	(0.00541)	(0.00338)
Nghe An	0.489	-0.0855***	-0.0174**	0.580*	0.0247**	0.0237***	0.0804	0.0205***	0.0202***
	(0.469)	(0.0156)	(0.00808)	(0.327)	(0.0114)	(0.00560)	(0.192)	(0.00549)	(0.00344)
Quang Nam	7.360***	0.156***	0.0831***	3.853***	0.123***	0.0636***	2.811***	0.0734***	0.0376***
	(0.463)	(0.0154)	(0.00800)	(0.324)	(0.0113)	(0.00556)	(0.190)	(0.00545)	(0.00341)
constant	2.882	0.196***	0.0725**	3.175**	0.110**	0.0548**	0.00136	0.0136	0.0134
	(2.050)	(0.0679)	(0.0352)	(1.431)	(0.0498)	(0.0245)	(0.839)	(0.0240)	(0.0150)
Observations	1563	1566	1573	1565	1568	1575	1565	1568	1575
Adjusted R^2	0.196	0.197	0.148	0.109	0.088	0.084	0.178	0.127	0.104

The numbers in parentheses are standard errors. * p <.10, ** p <.05, *** p <.01
Time-to-maturity—D: One day, M: One month, Y: One year.

Loan principal (in thousand VND)—100, 1000 and 4000.

For instance, 100D stands for a one-month loan with loan principal of 100,000 VND.

Table C.2: Regressions on credit constraint dummy variables

	100 D	100 M	100 Y	100	1000 M	1000 Y	4000 D	4000 M	4000 Y
CC only in 2006	0.602	0.0349	0.0274*	1.54	0.0307	0.00581	0.606*	0.0144	-0.00219
	(0.845)	(0.0281)	(0.0140)	(0.5	(0.0194)	(0.00943)	(0.342)	(0.00953)	(0.00585)
CC only in 2007	-0.363	0.0174	0.00996	1.06	0.0118	0.00617	0.451	0.00304	-0.00125
	(0.687)	(0.0228)	(0.0115)	(0.4	(0.0157)	(0.00771)	(0.278)	(0.00774)	(0.00479)
CC both in 2006 and	0.0536	0.0252*	0.0150**	0.09	0.0140	0.00447	0.137	0.00291	-0.00279
	(0.389)	(0.0129)	(0.00649	(0.2	(0.00889)	(0.00435)	(0.157)	(0.00438)	(0.00270)
Constant	2.599***	0.173***	0.105***	1.93	0.128***	0.0836***	1.298***	0.0815***	0.0616***
	(0.227)	(0.00755)	(0.00379	(0.1	(0.00521)	(0.00254)	(0.0919)	(0.00256)	(0.00158)
Observations	1563	1566	1573	15	1568	1575	1565	1568	1575
Adjusted R^2	-0.001	0.001	0.003	0.0	0.001	-0.001	0.002	-0.000	-0.001

The numbers in parentheses are standard errors. * $p < .10$, ** $p < .05$, *** $p < .01$

Time-to-maturity—D: One day, M: One month, Y: One year.

Loan principal (in thousand VND)—100, 1000 and 4000.

For instance, 100D stands for a one-month loan with loan principal of 100,000 VND.

Table C.3: Regressions on past loss experience variables

	100 D	100 M	100 Y	1000 D	1000 M	1000 Y	4000 D	4000 M	4000 Y
AI	1.011*	0.0292	0.0171*	0.980**	0.0238*	0.0182***	0.590**	0.0180***	0.0118***
	(0.589)	(0.0198)	(0.00990)	(0.396)	(0.0138)	(0.00668)	(0.237)	(0.00674)	(0.00416)
flood	2.812***	0.0531***	0.0218***	1.465***	0.0355***	0.00882*	1.401***	0.0242***	0.00397
	(0.419)	(0.0141)	(0.00713)	(0.283)	(0.00983)	(0.00483)	(0.169)	(0.00481)	(0.00301)
typhoon	2.291***	0.0497***	0.0181**	0.678**	0.0103	0.00343	0.719***	0.00910*	0.00287
	(0.424)	(0.0143)	(0.00723)	(0.287)	(0.00996)	(0.00489)	(0.171)	(0.00487)	(0.00305)
drought	-1.502**	-0.00898	0.0151	-0.0520	0.0420**	0.0243***	-0.247	0.0220***	0.00316
	(0.724)	(0.0243)	(0.0123)	(0.489)	(0.0170)	(0.00836)	(0.292)	(0.00832)	(0.00521)
hail	-1.943*	-0.0551	-0.0297*	-1.139	-0.0312	-0.00858	-0.966**	-0.0155	-0.00472
	(1.054)	(0.0354)	(0.0176)	(0.712)	(0.0248)	(0.0119)	(0.425)	(0.0121)	(0.00741)
landslide	-2.276	0.0295	0.0578	-0.228	-0.0321	-0.0210	0.448	0.00586	-0.0120
	(2.114)	(0.0710)	(0.0360)	(1.428)	(0.0497)	(0.0244)	(0.852)	(0.0243)	(0.0152)
other epidemics	0.471	0.0943***	0.0413***	0.583**	0.0307***	0.0129***	0.241	0.0117**	0.00643**
	(0.399)	(0.0134)	(0.00680)	(0.270)	(0.00937)	(0.00460)	(0.161)	(0.00458)	(0.00287)
others	-0.149	0.00678	-0.000678	0.758**	-0.00323	0.00340	-0.118	0.00113	0.00378
	(0.475)	(0.0159)	(0.00808)	(0.321)	(0.0111)	(0.00547)	(0.192)	(0.00545)	(0.00341)
constant	1.449***	0.136***	0.0909***	1.328***	0.114***	0.0766***	0.869***	0.0703***	0.0558***
	(0.261)	(0.00875)	(0.00443)	(0.176)	(0.00611)	(0.00299)	(0.105)	(0.00299)	(0.00187)
Observations	1563	1566	1573	1565	1568	1575	1565	1568	1575
Adjusted R^2	0.065	0.044	0.034	0.030	0.018	0.013	0.072	0.030	0.006

The numbers in parentheses are standard errors. * $p < .10$, ** $p < .05$, *** $p < .01$

Time-to-maturity—D: One day, M: One month, Y: One year.

Loan principal (in thousand VND)—100, 1000 and 4000.

For instance, 100D stands for a one-month loan with loan principal of 100,000 VND.

Table C.4: Regressions on the number of past AI/flood loss experiences

	100 D	100 M	100 Y	1000 D	1000 M	1000 Y	4000 D	4000 M	4000 Y
No. of AI	0.929**	0.0303*	0.0166**	0.639**	0.0140	0.0107**	0.482***	0.0124**	0.00698**
	(0.465)	(0.0155)	(0.00778)	(0.308)	(0.0107)	(0.00521)	(0.184)	(0.00522)	(0.00324)
No. of floods	1.431***	0.0321***	0.0141***	1.013***	0.0280***	0.00916***	0.986***	0.0180***	0.00252
	(0.273)	(0.00913)	(0.00460)	(0.181)	(0.00628)	(0.00308)	(0.109)	(0.00307)	(0.00192)
constant	2.096***	0.171***	0.106***	1.749***	0.125***	0.0818***	1.057***	0.0766***	0.0590***
	(0.194)	(0.00647)	(0.00326)	(0.128)	(0.00446)	(0.00219)	(0.0770)	(0.00218)	(0.00136)
Observations	1563	1566	1573	1565	1568	1575	1565	1568	1575
Adjusted R^2	0.020	0.010	0.008	0.023	0.013	0.008	0.056	0.026	0.003

The numbers in parentheses are standard errors. * $p < .10$, ** $p < .05$, *** $p < .01$ Time-to-maturity D: One day, M: One month, Y: One year.

Loan principal (in thousand VND)100, 1000 and 4000.

For instance, 100D stands for a one-month loan with loan principal of 100,000 VND

Table C.5: Regressions on the nature of past losses/damages

	100 D	100 M	100 Y	1000 D	1000 M	1000 Y	4000 D	4000 M	4000 Y
house lost	-3.537	-0.0657	-0.0506	-2.231	-0.000722	0.0134	-1.826	-0.0173	-0.0185
	(3.261)	(0.111)	(0.0566)	(2.240)	(0.0781)	(0.0384)	(1.328)	(0.0380)	(0.0238)
house damage	6.419***	0.129***	0.0440***	2.029***	0.0343***	0.00551	2.049***	0.0283***	-0.000449
	(0.503)	(0.0171)	(0.00873)	(0.346)	(0.0121)	(0.00592)	(0.205)	(0.00587)	(0.00367)
phys assets loss	-0.452	-0.0287	-0.00412	-0.159	-0.00505	0.00207	-0.0663	-0.00572	0.00394
	(0.665)	(0.0225)	(0.0115)	(0.456)	(0.0159)	(0.00782)	(0.271)	(0.00775)	(0.00485)
phys livestock loss	0.690*	0.0742***	0.0261***	0.775***	0.0280***	0.00877**	0.609***	0.0154***	0.00311
	(0.368)	(0.0125)	(0.00636)	(0.252)	(0.00879)	(0.00431)	(0.150)	(0.00428)	(0.00267)
econ livestock loss	0.739	0.0639***	0.0293**	0.0955	0.0113	0.0151*	1.265***	0.0272***	0.0213***
	(0.717)	(0.0243)	(0.0123)	(0.493)	(0.0172)	(0.00835)	(0.292)	(0.00837)	(0.00518)
harvest loss	0.0300	0.00772	0.0106*	0.708***	0.0289***	0.0149***	0.193	0.0143***	0.00722***
	(0.340)	(0.0115)	(0.00589)	(0.234)	(0.00814)	(0.00399)	(0.139)	(0.00397)	(0.00248)
human casualty	-2.070	-0.000366	-0.0142	-1.002	-0.0151	-0.0226	-0.500	0.00886	0.00654
	(2.681)	(0.0909)	(0.0465)	(1.842)	(0.0642)	(0.0316)	(1.092)	(0.0313)	(0.0196)
human sickness/injury	2.056	0.181***	0.107***	3.166**	0.0668	0.0371	2.318***	0.0373*	0.00749
	(1.924)	(0.0652)	(0.0334)	(1.321)	(0.0461)	(0.0226)	(0.783)	(0.0224)	(0.0140)
others	-1.124	-0.0761	-0.0259	0.414	-0.00440	-0.00341	0.201	0.0169	0.0101
	(1.378)	(0.0467)	(0.0239)	(0.947)	(0.0330)	(0.0162)	(0.561)	(0.0161)	(0.0101)
constant	1.568***	0.141***	0.0925***	1.329***	0.110***	0.0753***	0.797***	0.0678***	0.0551***
	(0.258)	(0.00873)	(0.00446)	(0.177)	(0.00616)	(0.00302)	(0.105)	(0.00300)	(0.00188)
Observations	1563	1566	1573	1565	1568	1575	1565	1568	1575
Adjusted R^2	0.099	0.062	0.035	0.034	0.016	0.010	0.088	0.036	0.012

The numbers in parentheses are standard errors. * $p < .10$, ** $p < .05$, *** $p < .01$ Time-to-maturity—D: One day, M: One month, Y: One year.
Loan principal (in thousand VND)—100, 1000 and 4000.
For instance, 100D stands for a one-month loan with loan principal of 100,000 VND.

Table C.6: Regressions on attitude towards risk

	100 D	100 M	100 Y	1000 D	1000 M	1000 Y	4000 D	4000 M	4000 Y
moderately risk averse	-0.179	-0.0398**	-0.0212**	0.27	-0.0203*	-0.00264	0.283	-0.00592	0.000308
	(0.503)	(0.0168)	(0.00847)	(0.337)	(0.0116)	(0.00568)	(0.206)	(0.00573)	(0.00353)
risk loving 1	2.630***	0.0600***	0.0150**	0.359	0.00298	0.00755	0.107	-0.00102	0.000872
	(0.425)	(0.0142)	(0.00718)	(0.285)	(0.00986)	(0.00482)	(0.174)	(0.00485)	(0.003)
constant	2.075***	0.177***	0.112***	2.003***	0.137***	0.0844***	1.338***	0.0844***	0.0603***
	(0.215)	(0.00716)	(0.00362)	(0.144)	(0.00498)	(0.00243)	(0.0881)	(0.00245)	-0.00151
Observations Adjusted R2	1557	1560	1567	1559	1562	1569	1559	1562	1569
	0.025	0.017	0.007	0	0.001	0.001	0	-0.001	-0.001

The numbers in parentheses are standard errors. * p <.10, ** p <.05, *** p < .01
Time-to-maturity—D: One day, M: One month, Y: One year.
Loan principal (in thousand VND)—100, 1000 and 4000.
For instance, 100D stands for a one-month loan with loan principal of 100,000 VND.

Table C.7: Regression on loss aversion types

	100 D	100 M	100 Y	1000 D	1000 M	1000 Y	4000 D	4000 M	4000 Y
loss averse	0.0354	-0.0219*	-0.00358	-0.238	0.0132	0.00821*	0.243	0.00806*	0.00556**
	(0.391)	(0.0130)	(0.00659)	(0.262)	(0.00904)	(0.00441)	(0.160)	(0.00445)	(0.00274)
risk loving 2	2.692***	0.0580***	0.0174**	0.208	0.0131	0.0119**	0.171	0.00397	0.00314
	(0.452)	(0.0151)	(0.00764)	(0.304)	(0.0105)	(0.00512)	(0.185)	(0.00515)	(0.00318)
constant	2.026***	0.180***	0.109***	2.161***	0.127***	0.0801***	1.279***	0.0796***	0.0579***
	(0.264)	(0.00878)	(0.00445)	(0.177)	(0.00610)	(0.00298)	(0.108)	(0.00300)	(0.00185)
Observations	1556	1559	1566	1558	1561	1568	1558	1561	1568
Adjusted R^2	0.025	0.016	0.004	0.000	0.000	0.003	0.000	0.001	0.001

The numbers in parentheses are standard errors. * p < .10, ** p < .05, *** p <.01
Time-to-maturity D: One day, M: One month, Y: One year.
Loan principal (in thousand VND)100, 1000 and 4000.
For instance, 100D stands for a one-month loan with loan principal of 100,000 VND.

Table C.8: Regressions on income change

	100 D	100 M	100 Y	1000 D	1000 M	1000 Y	4000 D	4000 M	4000 Y
change in income	-0.631	-0.0912*	-0.0317	-3.678***	-0.198***	-0.0820***	-2.043***	-0.0637***	-0.0198*
	(1.611)	(0.0535)	(0.0270)	(1.064)	(0.0366)	(0.0179)	(0.650)	(0.0181)	(0.0112)
constant	3.316*	0.285***	0.147***	6.193***	0.354***	0.177***	3.664***	0.154***	0.0825***
	(1.794)	(0.0596)	(0.0300)	(1.185)	(0.0407)	(0.0200)	(0.724)	(0.0201)	(0.0125)
Observations	1563	1566	1573	1565	1568	1575	1565	1568	1575
Adjusted R^2	-0.001	0.001	0.000	0.007	0.018	0.012	0.006	0.007	0.001

The numbers in parentheses are standard errors. * p < .10, ** p < .05, *** p < .01
Time-to-maturity—D: One day, M: One month, Y: One year.
Loan principal (in thousand VND)—100, 1000 and 4000.
For instance, 100D stands for a one-month loan with loan principal of 100,000 VND.

D. Estimation results of the Euler equations

Table D.1: Estimation of ρ: No credit constraints

	(1) Simple	(2) Tanaka	(3) Fitted
ρ	0.000197***	0.000198***	0.000172***
	(0.00000410)	(0.00000508)	(0.00000347)
Observations	14064	14064	14118

The numbers in parentheses are standard errors. $*p<.10$, $**p<.05$, $***p<.01$

βisset at0.99.

Table D.2: Estimation of β: No credit constraints

	(1) Simple	(2) Tanaka	(3) Fitted
β	0.991***	0.990***	0.994***
	(0.000621)	(0.000768)	(0.000524)
Observations	14064	14064	14118

The numbers in parentheses are standard errors. $*p<.10$, $**p<.05$, $***p<.01$
ρ is set at 0.0002.

Table D.3: Estimation of ρ: With subjective credit constraints

	(1) Simple	(2) Tanaka	(3) Fitted	(4) Simple	(5) Tanaka	(6) Fitted	(7) Simple	(8) Tanaka	(9) Fitted
ρ_0	0.000141***	0.000125***	0.000109***	0.000195***	0.000232***	0.000181***	0.000156***	0.000143***	0.000113***
	(0.0000135)	(0.0000169)	(0.0000102)	(0.0000171)	(0.0000153)	(0.0000105)	(0.0000208)	(0.0000238)	(0.0000148)
ρ_1: CCin2007	0.000179***	0.000260***	0.000178***				0.000479***	0.000362***	0.000558***
	(0.0000407)	(0.0000568)	(0.0000272)				(0.0000903)	(0.0000751)	(0.0000692)
λ: CCin2007				0.00390	0.00139	0.000509	-0.0180***	-0.00404*	-0.00909***
				(0.00253)	(0.00165)	(0.000671)	(0.00500)	(0.00219)	(0.00141)
λ: CCin2007*asset				0.000000845***	0.000000276	0.000000185**	0.000000579*	0.000000316	0.000000146
				(0.000000277)	(0.000000193)	(8.62e-08)	(0.000000331)	(0.000000224)	(0.000000115)
λ: CCin2007*income				-0.000000241*	-0.000000249***	-6.19e-08*	-5.86e-08	-6.14e-08	3.56e-08
				(0.000000126)	(8.18e-08)	(3.55e-08)	(0.000000146)	(9.83e-08)	(4.52e-08)
Observations	14064	14064	14118	14064	14064	14118	14064	14064	14118

The numbers in parentheses are standard errors. $*p<.10$, $**p<.05$, $***p<.01$
β is set at 0.99

Table D.4: Estimation of β: With subjective credit constraints

	(1) Simple	(2) Tanaka	(3) Fitted	(4) Simple	(5) Tanaka	(6) Fitted	(7) Simple	(8) Tanaka	(9) Fitted
β_0	0.999***	1.001***	1.004***	0.991***	0.986***	0.994***	0.997***	0.998***	1.003***
	(0.00205)	(0.00252)	(0.00155)	(0.00259)	(0.00225)	(0.00158)	(0.00280)	(0.00345)	(0.00181)
β_1: CCin2007	-0.0256***	-0.0373***	-0.0266***				-0.0652***	-0.0542***	-0.0795***
	(0.00597)	(0.00803)	(0.00399)				(0.0107)	(0.0101)	(0.00747)
λ: CCin2007				0.00398	0.00136	0.000620	-0.0177***	-0.00483**	-0.00903***
				(0.00253)	(0.00165)	(0.000670)	(0.00446)	(0.00210)	(0.00116)
λ: CCin2007*asset				0.000000848***	0.000000278	0.000000197**	0.000000580*	0.000000298	0.000000124
				(0.000000277)	(0.000000194)	(8.59e-08)	(0.000000297)	(0.000000211)	(9.52e-08)
λ: CCin2007*income				-0.000000232*	-0.000000235***	-5.80e-08	-2.91e-08	-5.26e-08	3.08e-08
				(0.000000127)	(8.14e-08)	(3.54e-08)	(0.000000132)	(9.39e-08)	(3.66e-08)
Observations	14064	14064	14118	14064	14064	14118	14064	14064	14118

The numbers in parentheses are standard errors. $*p<.10$, $**p<.05$, $***p<.01$

ρ is set at 0.0002.

Table D.5: Estimation of ρ: Credit constraints represented by disaster loss experiences

	(1) Simple	(2) Tanaka	(3) Fitted	(4) Simple	(5) Tanaka	(6) Fitted	(7) Simple	(8) Tanaka	(9) Fitted
ρ_0	0.000169***	0.000168***	0.000139***	0.000184***	0.000175***	0.000149***	0.000196***	0.000183***	0.000151***
	(0.00000572)	(0.00000716)	(0.00000473)	(0.0000109)	(0.0000126)	(0.00000937)	(0.0000145)	(0.0000173)	(0.00000936)
ρ_1: AI	0.0000433**	0.0000496**	0.0000557***				0.000129	0.000000323	-0.000445**
	(0.0000202)	(0.0000214)	(0.0000166)				(0.000363)	(0.000186)	(0.000218)
ρ_1: flood	0.0000885***	0.0000791***	0.000113***				0.000220	0.0000756	0.000705***
	(0.0000148)	(0.0000159)	(0.0000127)				(0.000207)	(0.000133)	(0.000170)
λ: AI				0.0158	0.00871	0.00370	0.0143	0.0115	0.00514
				(0.0126)	(0.00663)	(0.00461)	(0.0194)	(0.00870)	(0.00806)
λ: flood				-0.00325	0.00345	-0.00297	-0.0221	-0.00178	-0.0131***
				(0.00963)	(0.00583)	(0.00294)	(0.0191)	(0.0103)	(0.00440)
λ: AI*asset				0.0000222***	0.0000111**	0.00000701***	0.0000195**	0.0000103**	-0.00000261
				(0.00000813)	(0.00000473)	(0.00000251)	(0.00000787)	(0.00000461)	(0.00000309)
λ: flood*asset				-0.00000887***	-0.00000438**	-0.00000300***	-0.00000791**	-0.00000412**	0.00000102
				(0.00000323)	(0.00000192)	(0.00000101)	(0.00000315)	(0.00000186)	(0.00000123)
λ: AI*income				-0.00000258**	-0.00000126*	-0.000000784**	-0.00000269**	-0.00000132**	0.000000642
				(0.00000110)	(0.000000660)	(0.000000337)	(0.00000116)	(0.000000662)	(0.000000422)
λ: flood*income				0.00000133**	0.000000466	0.000000607***	0.00000125**	0.000000471	-0.000000257
				(0.000000646)	(0.000000388)	(0.000000193)	(0.000000622)	(0.000000378)	(0.000000227)
Observations	14064	14064	14118	14064	14064	14118	14064	14064	14118

The numbers in parentheses are standard errors. $*p<.10$, $**p<.05$, $***p<.01$

β is set at 0.99.

Table D.6: Estimation of β: Credit constraints represented by disaster loss experiences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Simple	Tanaka	Fitted	Simple	Tanaka	Fitted	Simple	Tanaka	Fitted
β_0	0.995***	0.995***	0.999***	0.992***	0.994***	0.998***	0.991***	0.993***	0.998***
	(0.000871)	(0.00109)	(0.000727)	(0.00165)	(0.00189)	(0.00141)	(0.00223)	(0.00262)	(0.00122)
β_1: AI	-0.00658**	-0.00742**	-0.00839***				-0.0155	0.00407	0.0526**
	(0.00304)	(0.00324)	(0.00256)				(0.0500)	(0.0279)	(0.0268)
β_1: flood	-0.0132***	-0.0119***	-0.0170***				-0.0332	-0.0119	-0.0981***
	(0.00225)	(0.00242)	(0.00195)				(0.0281)	(0.0195)	(0.0161)
λ: AI				0.0157	0.00854	0.00374	0.0158	0.0121	0.00221
				(0.0126)	(0.00659)	(0.00458)	(0.0185)	(0.00859)	(0.00575)
λ: flood				-0.00311	0.00359	-0.00299	-0.0226	-0.00162	-0.0130***
				(0.00958)	(0.00577)	(0.00291)	(0.0185)	(0.0102)	(0.00313)
λ: AI*asset				0.0000220***	0.0000109**	0.00000699***	0.0000191**	0.0000102**	-0.00000268
				(0.00000809)	(0.00000470)	(0.00000248)	(0.00000763)	(0.00000459)	(0.00000247)
λ: flood*asset				-0.00000882***	-0.00000434**	-0.00000300***	-0.00000777**	-0.00000406**	0.00000101
				(0.00000322)	(0.00000190)	(0.000000993)	(0.00000305)	(0.00000186)	(0.000000989)
λ: AI*income				-0.00000256**	-0.00000124*	-0.000000785**	-0.00000264**	-0.00000127*	0.000000630*
				(0.00000109)	(0.000000655)	(0.000000334)	(0.00000113)	(0.000000659)	(0.000000331)
λ: flood*income				0.00000132**	0.000000457	0.000000607***	0.00000124**	0.000000457	-0.000000262
				(0.000000643)	(0.000000384)	(0.000000192)	(0.000000605)	(0.000000375)	(0.000000185)
Observations	14064	14064	14118	14064	14064	14118	14064	14064	14118

The numbers in parentheses are standard errors. *p<.10, **p<.05, ***p<.01
ρ is set at 0.0002

Table D.7: Estimation of ρ: Credit constraints represented by nature of damage/losses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Simple	Tanaka	Fitted	Simple	Tanaka	Fitted	Simple	Tanaka	Fitted
ρ_0	0.000155***	0.000155***	0.000113***	0.000125***	0.000128***	0.0000972***	0.000141***	0.000113***	0.0000605*
	(0.00000993)	(0.0000119)	(0.00000938)	(0.0000199)	(0.0000274)	(0.0000178)	(0.0000440)	(0.0000376)	(0.0000339)
ρ_1: house damage	0.000137***	0.000123***	0.000152***				-0.000440	-0.000258	-0.000528*
	(0.0000226)	(0.0000266)	(0.0000195)				(0.000590)	(0.000365)	(0.000315)
ρ_1: phys livestock loss	0.0000424***	0.0000362**	0.0000592***				-0.000873*	-0.000474*	0.0000833
	(0.0000135)	(0.0000159)	(0.0000110)				(0.000482)	(0.000286)	(0.000214)
ρ_1: harvest loss	0.0000352*	0.0000388	0.0000554**				0.000586	0.000390*	0.000318
	(0.0000214)	(0.0000238)	(0.0000220)				(0.000365)	(0.000227)	(0.000196)
λ_1: house damage				0.0406**	0.0275*	0.0171**	-0.0117	-0.00868	0.0359**
				(0.0202)	(0.0152)	(0.00730)	(0.0785)	(0.0364)	(0.0165)
λ_1: phys livestock loss				0.0214**	0.0164**	0.00658**	0.0464**	0.00935	0.00309
				(0.00961)	(0.00720)	(0.00328)	(0.0231)	(0.0126)	(0.00496)
λ_1: harvest loss				-0.0111	-0.0118	-0.00646	0.00252	0.0102	-0.0103*
				(0.0128)	(0.00925)	(0.00454)	(0.0251)	(0.0182)	(0.00608)
λ_1: house damage*asset				0.000000629	-0.00000226	-0.000000713	0.00000885	0.00000198	0.00000238
				(0.00000388)	(0.00000278)	(0.00000127)	(0.0000118)	(0.00000639)	(0.00000214)
λ_1: phys livestock loss*asset				-0.00000821***	-0.00000628***	-0.00000344***	0.00000397	0.000000226	-0.00000355**
				(0.00000216)	(0.00000176)	(0.000000838)	(0.00000847)	(0.00000417)	(0.00000157)
λ_1: harvest loss*asset				0.00000543***	0.00000483***	0.00000257***	-0.00000555	-0.00000106	0.00000184*
				(0.00000178)	(0.00000142)	(0.000000689)	(0.00000815)	(0.00000410)	(0.00000110)
λ_1: house damage*income				-0.00000137	-0.000000696	-0.000000392	0.00000173	0.000000955	-0.000000813*
				(0.000000889)	(0.000000659)	(0.000000315)	(0.00000286)	(0.00000138)	(0.000000422)
λ_1: phys livestock loss*income				0.000000190	8.62e-08	0.000000172	0.00000125	0.000000832	0.000000260
				(0.000000372)	(0.000000288)	(0.000000132)	(0.00000127)	(0.000000787)	(0.000000244)
λ_1: harvest loss*income				0.000000130	0.000000110	8.16e-08	-0.00000137	-0.000000951	0.000000110
				(0.000000444)	(0.000000323)	(0.000000153)	(0.00000123)	(0.000000745)	(0.000000215)
Observations	14064	14064	14118	14064	14064	14118	14064	14064	14118

The numbers in parentheses are standard errors. *p<.10, **p<.05, ***p<.01
β is set at 0.99.

Table D.8: Estimation of β: Credit constraints represented by nature of damage

	(1) Simple	(2) Tanaka	(3) Fitted	(4) Simple	(5) Tanaka	(6) Fitted	(7) Simple	(8) Tanaka	(9) Fitted
β_0	0.997***	0.997***	1.003***	1.001***	1.001***	1.006***	1.003***	1.006***	1.012***
	(0.00150)	(0.00180)	(0.00144)	(0.00296)	(0.00412)	(0.00263)	(0.00364)	(0.00519)	(0.00474)
β_1: house damage	-0.0205***	-0.0182***	-0.0227***				0.0578	0.0424	0.0855*
	(0.00330)	(0.00391)	(0.00287)				(0.0563)	(0.0463)	(0.0474)
β_1: phys livestock loss	-0.00654***	-0.00559**	-0.00886***				0.139**	0.0793**	-0.0110
	(0.00204)	(0.00240)	(0.00166)				(0.0561)	(0.0401)	(0.0283)
β_1: harvest loss	-0.00500	-0.00577	-0.00780**				-0.0945**	-0.0641**	-0.0496*
	(0.00322)	(0.00361)	(0.00336)				(0.0434)	(0.0319)	(0.0262)
λ_1: house damage				0.0405**	0.0276*	0.0169**	-0.0140	-0.00702	0.0345**
				(0.0196)	(0.0149)	(0.00707)	(0.0462)	(0.0289)	(0.0145)
λ_1: phys livestock loss				0.0214**	0.0164**	0.00674**	0.0425**	0.00765	0.00283
				(0.00930)	(0.00701)	(0.00314)	(0.0168)	(0.0119)	(0.00412)
λ_1: harvest loss				-0.0111	-0.0117	-0.00643	0.00483	0.0117	-0.00970*
				(0.0125)	(0.00903)	(0.00439)	(0.0189)	(0.0164)	(0.00521)
λ_1: house damage*asset				0.000000656	-0.00000221	-0.000000694	0.00000722	0.00000153	0.00000255
				(0.00000374)	(0.00000270)	(0.00000121)	(0.00000772)	(0.00000532)	(0.00000182)
λ_1: phys livestock loss*asset				-0.00000815***	-0.00000628***	-0.00000346***	0.00000393	0.000000173	-0.00000346***
				(0.00000208)	(0.00000171)	(0.000000798)	(0.00000624)	(0.00000369)	(0.00000123)
λ_1: harvest loss*asset				0.00000539***	0.00000482***	0.00000257***	-0.00000512	-0.000000942	0.00000171*
				(0.00000172)	(0.00000137)	(0.000000650)	(0.00000588)	(0.00000362)	(0.000000885)
λ_1: house damage*income				-0.00000136	-0.000000708	-0.000000383	0.00000159	0.000000920	-0.000000767**
				(0.000000865)	(0.000000646)	(0.000000307)	(0.00000184)	(0.00000114)	(0.000000373)
λ_1: phys livestock loss*income				0.000000184	9.17e-08	0.000000167	0.00000124	0.000000964	0.000000275
				(0.000000362)	(0.000000281)	(0.000000126)	(0.000000799)	(0.000000650)	(0.000000202)
λ_1: harvest loss*income				0.000000134	0.000000110	8.11e-08	-0.00000147	-0.00000105	8.58e-08
				(0.000000431)	(0.000000316)	(0.000000148)	(0.000000940)	(0.000000677)	(0.000000187)
Observations	14064	14064	14118	14064	14064	14118	14064	14064	14118

The numbers in parentheses are standard errors. *p<.10, **p<.05, ***p<.01
ρ is set at 0.0002

CHAPTER 6

How to Strengthen Social Capital in Disaster Affected Communities? The Case of the Great East Japan Earthquake

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In this paper, we investigate two important issues regarding the design and implementation of appropriate disaster management and reconstruction policies. First, we examine the nexus between damage caused by a disaster and preference parameters. Second, we study the impact of individual preference on social capital. With this aim, we employed unique field experiment data collected exclusively for this study from the residents of Iwanuma city, located near Sendai city in Miyagi Prefecture, Japan, who were affected by the March 11th, 2011 earthquake and tsunami. We conducted carefully designed artefactual experiments using the methodology of the Convex Time Budget (CTB) experiments of Andreoni and Sprenger (2012) to elicit present bias, time discount, and risk preference parameters. We also conducted canonical dictator and public goods games to capture the pro-social behaviour, or simply "social capital" of the subjects of the experiments. Four important findings emerged. First, we found an absence of quasi-hyperbolic discounting in the whole sample. Second, we found that disaster damage seems to make individuals more present-biased, although the change observed is not necessarily statistically significant. Third, in dictator games, the amounts sent to victims of the Great East Japan Earthquake were larger than those sent to anonymous persons in Japan. Also, we found that present bias parameter and time discount factor were both negatively related to the amount of donation, implying that seemingly altruistic behaviours might be driven by myopic preference. Finally, we found that present bias is closely related to bonding social capital.

Keywords: Convex Time Budget experiment, Natural Disaster, Risk and Time Preference
JEL Classification: C93,D81,O12.

1. Introduction

On March 11th, 2011, an earthquake measuring 9.0 on the Richter scale off the shore of Japan's northeastern coast in Tohoku caused a tsunami with a maximum height of more than 20 meters (65 feet), which devastated coastal communities. The disaster also shut down the cooling systems and backup generators at the Fukushima Dai-ichi nuclear power plant. The tsunami resulted in the loss of more than 21,500 lives, and the complete destruction of over one-hundred-thousand buildings. While the Great East Japan is admittedly one of the most serious disasters in human history, a variety of disasters hit different parts of the world, too. It has become clear that only a small proportion of damage caused by natural disasters was covered by formal insurance schemes. Can we really protect our livelihoods from catastrophes? What is the role of different market and non-market insurance mechanisms? What lessons can we learn from the aftermath of disasters? This paper tries to provide rigorous evidence to answer some of these questions.

In response to the wide variety of shocks caused by natural disasters, including earthquakes, individuals have developed formal and informal mechanisms to deal with the potential negative consequences. In general, there are two mechanisms: ex-ante risk management and ex-post risk-coping behaviours. Risk management strategies can be defined as the actions of households to mitigate risk and shock before the resolution of uncertainties, including accumulation of precautionary savings, taking out formal disaster insurance such as earthquake insurance, and investment in mitigation such as earthquake-proof housing structures. Even if households adopt a variety of risk management strategies, disasters tend to strike unexpectedly and can have a serious negative impact on household welfare. Therefore, ex-post risk-coping strategies those used to mitigate the downside impacts of shocks to livelihood once a disaster has struck will be needed. Risk coping strategies can take the form of market insurance mechanisms such as receiving insurance payouts, borrowing, and obtaining additional employment; self-insurance mechanisms; and non-market insurance mechanisms provided by government and communities. In theory, idiosyncratic shocks to a household should be absorbed by all other members in the same insurance network and should therefore not affect livelihoods. Market, state, and community mechanisms have the potential to function effectively to minimise the damage caused by disasters. To be able to strengthen these mechanisms, we need to clearly understand the roles of individual and social preferences. To identify effective policies geared towards facilitating livelihood recovery of the victims of a disaster, it is necessary to clarify how individual and social preferences are affected by the disaster.

Individual preference parameters have traditionally been treated as "deep parameters" in economics, i.e., not determined by economic decisions, and therefore constant over time (e.g., Stigler and Becker, 1977). More recently, studies on endogenous formation of individual and social preferences have found that they are not constant over time and that they change under certain circumstances (Fehr and Hoff, 2011). As natural disasters and manmade disasters are traumatic events, they are likely to affect the behaviour of individuals in the short term and possibly the long term. Examples are the studies by Cameron and Shah (2011) and Cassar, *et al.* (2011) on the Indian Ocean tsunami in 2004. Cameron and Shah (2011) found that individuals in Indonesia who suffered a flood or earthquake in the past three years are more risk averse than those who were not affected by a flood or earthquake. Cassar, *et al.* (2011) showed that, after the tsunami in Thailand, individuals affected by the disaster were substantially more trusting, more risk averse and more trustworthy. From these results, they concluded that individual welfare and aggregate growth levels are affected by the change in these social preferences. Callen, *et al.* (2014), investigating the relationship between violence and economic risk preferences in Afghanistan, found a strong preference for certainty and violation of the expected utility framework. Voors, *et al.* (2012) used a series of field experiments in rural Burundi to find that individuals exposed to violence display more altruistic behaviour towards their neighbours and are more risk-seeking: the results indicate that large shocks can have long-term consequences for insurance mechanisms.

In this study, we use the natural experimental situation that emerged in the wake of the March 11th, 2011 earthquake and tsunami disaster in Japan to investigate the nexus between damage caused by the disaster and preference parameters. We also examine how individual preference parameters affect the social capital of disaster-affected people. More specifically, we use unique field experiment data collected from the tsunami-affected residents of

Iwanuma city, located near Senday city in Miyagi Prefecture. We conducted carefully designed artefactual experiments using the methodology of the Convex Time Budget (CTB) experiments of Andreoni and Sprenger (2012) and conducted canonical dictator and public goods games to elicit the extent of individual pro-social behaviour. With the present bias, time discount, and risk preference parameters, as well as the level of social capital identified, we investigated the impact of the damage caused by the earthquake and tsunami.

2. Earthquakes in Japan

Japan is vulnerable to a wide variety of natural disasters such as earthquakes, tsunamis, volcanic eruptions, typhoons, floods, landslides, and avalanches. Of these natural disasters, earthquakes are the most serious and frequently occurring (Sawada, 2013). Japan's continuous earthquake activity is due to the country's location on a subduction zone, where four of the more than 10 tectonic plates covering the globe are crushed against each other. Indeed, of the 912 earthquakes with a magnitude of 6.0 on the Richter scale or greater that occurred worldwide between 1996 and 2005, 190 occurred in or around Japan, meaning that more than 20 percent of the world's large earthquakes took place in or around Japan.

Throughout Japan's history, earthquakes have regularly hit the country: a total of 248 large earthquakes have occurred in Japan in the 1,300 years since the Hakuho earthquakes of 684, the oldest Japanese earthquakes to have been recorded in written form. Moreover, in the Nankai and Tokai areas, large earthquakes occur regularly every 100 to 200 years (”the twin earthquake”). In terms of human losses, the worst earthquake in the country's history was the Great Kanto earthquake of September 1st, 1923, which had a magnitude of 7.9 on the Richter scale. Large parts of Tokyo and Kanagawa were destroyed, several hundred thousand homes and buildings were in ruins, and more than 140,000 people were killed or went missing. The fires that followed the quake spread rapidly as many houses and other buildings were made of wood. In Tokyo, 477,128 houses, or 70 percent of the total, burnt down, with the fire blazing for a full three days. Thus some 44 percent of

Japan's gross domestic product (GDP) in 1922 was lost either directly as a result of the earthquake, or indirectly due to the fires, aftershocks, and tsunamis. Aiming never to forget the lessons of the Great Kanto earthquake, the Japanese government declared September 1st an annual day of earthquake disaster prevention exercises and related activities.

Since this time, through the development of disaster management systems and enhanced disaster information communication systems, the death toll and number of missing persons from disasters, most particularly earthquakes, has declined, with the two notable exceptions of the Great East Japan earthquake in 2011 and the Great Hanshin-Awaji (Kobe) earthquake in 1995. Particularly, we see vividly the 2011 devastating earthquake, tsunami, and nuclear radiation crisis in Japan that has killed tens of thousands people and resulting in damage of around 200 to 300 billion dollars. These two exceptions highlight the significance of natural disasters which can generate the most serious consequences ever known (Sawada, 2013).

The Kobe earthquake struck at 5:46 a.m. on January 17th, 1995, hitting an area that is home to 4 million people and contains one of Japan's main industrial clusters. The earthquake, which registered 7.3 on the Richter scale, cost 6,432 lives excluding 3 missing persons, resulted in 43,792 injured, and damaged 639,686 buildings, of which 104,906 were completely destroyed (Fire and Disaster Management Agency, 2006). Together with Hurricane Katrina, the Kobe earthquake caused the largest economic loss due to a natural disaster in history. The loss in housing property amounted to more than USD 60 billion, while that in capital stock exceeded USD 100 billion (Horwich, 2000).

The Great East Japan Earthquake of March 11th, 2011, itself caused relatively little damage to the residents and buildings in the northeast region of Japan known as Tohoku. However, the massive thrust-fault set off a tsunami with a maximum height of more than 20 meters (65 feet) which devastated coastal communities and shut down the cooling systems and backup generators at the Fukushima Dai-ichi nuclear power plant. The March 11 disaster resulted in the loss of more than 21,500 lives, and the complete destruction of over one hundred thousand buildings.

3. Data

We collected our experimental data in Iwanuma City in Miyagi Prefecture, which is located next to Sendai city and hosts Sendai airport. The city suffered enormous damage from the March 11th 2011 Great East Japan Earthquake, in part because the city faces the ocean and its terrain is quite flat. One-hundred-eighty lives were lost and 2,766 homes either collapsed or were seriously damaged in the city. Of all the areas affected by the tsunami, the proportion of the area submerged by the tsunami wave was the largest in Iwanuma city.

The survey and experimental data we used were collected exclusively for the study. The subjects were selected from the respondents of the Japan Gerontological Evaluation Study (JAGES), a survey conducted in November 2013 among residents aged 65 and over. From the 1,032 residents who agreed to participate in the experiments, we selected 346 respondents who lived in the tsunami affected areas. A total of 187 individuals participated in our field experiments conducted on 15 May (39 participants), 26 May (47 participants), 19 May (29 participants), 20 May (47 participants), and 21 May (25 participants).

4. Parameter Estimation Strategies

To elicit present bias, time discount, and risk aversion parameters, we carefully designed and conducted Convex Time Budget (CTB) experiments as set out in Andreoni and Sprenger (2012) and Andreoni, *et al.* (2013). We employed the data collected by the CTB experiments to separately identify the three key parameters of the utility function: risk aversion parameter, α; time discounting parameter, δ; and present bias parameter, β. As a theoretical framework, we assume a quasi-hyperbolic discounting structure for discounting and the preferences described by:

$$U(x) = u(x_t) + \beta \sum_{k=1}^{\infty} \delta^k u(x_{t+k}) \qquad (1)$$

where we postulate a constant relative risk aversion (CRRA) utility, $u(x_{t+k}) = x_{t+k}^{\alpha}$, the parameter δ captures standard long-run exponential discounting, and the parameter β captures a specific preference towards payments in the present, *t* = 0. While present bias is associated with β < 1, β = 1 corresponds to the case of standard exponential discounting.

In the CTB experiment, subjects are given the choice of (*X*, 0), (0, *Y*) or anywhere along the intertemporal budget constraint connecting these points such that $Px_t + x_{t+k} = Y$, where $P = \frac{Y}{X}$ is the gross interest rate. A standard intertemporal Euler equation maintains:

$$MRS = \frac{x_t^{\alpha-1}}{\beta^{\mathbf{1}\{t=t_0\}} \delta^k x_{t+k}^{\alpha-1}} = P \qquad (2)$$

where t_0 is an indicator for whether t = 0. This can be rearranged to be linear in these experimental variations, t, k, and P,

$$ln(\frac{x_t}{x_{t+k}}) = \frac{ln(\beta)}{\alpha - 1} t_0 + \frac{ln(\delta)}{\alpha - 1} k + \frac{1}{\alpha - 1} ln(P) \qquad (3)$$

Assuming an additive error structure, this is estimable at either the group or individual level. We employ the ordinary least squares (OLS) method to estimate the model given by equation (3).

However, the allocation ratio $ln(\frac{x_t}{x_{t+k}})$ is not well defined at corner solutions. To address this problem, we can use the demand function to generate a non-linear regression equation based on

$$x_t = \frac{10,000(\beta^{t_0} \delta^k P)^{\frac{1}{\alpha-1}}}{1 + P(\beta^{t_0} \delta^k P)^{\frac{1}{\alpha-1}}} \qquad (4)$$

which avoids the problem of the logarithmic transformation in (2). We can estimate the model of equation (4) by employing the non-linear least squares (NLS) method.

5 Results

5.1. The Covex Time Budget (CTB) Experiment

Table 6.1 presents the estimation results of aggregated-level homogenous risk aversion parameter, α; time discounting parameter, δ; and present bias parameter, β. The first two columns report the estimated parameter based on equation (4) using NLS and the last column shows results based on equation (3) using OLS. In all specifications, with the estimated present bias parameter and its standard error, we cannot reject the null hypothesis in which the present bias parameter equals one, indicating the absence of quasi-hyperbolic discounting in the whole sample. Moreover, the estimated time discount rate is close to zero and the estimated risk aversion parameter is within a reasonable range. Overall, we can safely say that the subjects from Iwanuma city used in our survey are forward-looking and patient without obvious present bias.

Table 6.1: The Results in Aggregate CTB

	(1) NLS w/o clustering	(2) NLS w/ clustering	(3) OLS
β	1.000***	1.000***	1.009***
	(0.00646)	(0.00674)	(0.0187)
δ	0.999***	0.999***	1.001***
	(0.0000947)	(0.000168)	(0.000597)
α	0.866***	0.868***	0.896***
	(0.00480)	(0.0102)	(0.00612)
N	4474	4450	4450

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Based on the data from the CTB experiments, we can also estimate the individual-level preference parameters. The distributions of all individual preference parameters are shown in Table 6.2. While discount factor and risk parameters are clustered, we can see large variations in the present bias and risk preference parameters. To investigate determinants of these parameters, we combine data of home and livelihood damage caused by the earthquake and tsunami, which are supposed to be exogenously determined.

Table 6.2: Summary Statiistics w.o. Outliers

Variable	Obs	Mean	Std. Dev.	P5	P10	P25	P50	P75	P90	P95
presentbias	185	1.25	1.069	.572	.752	.927	1.055	1.218	1.854	1.854
discountfactor	185	1.006	.028	.988	.994	.997	1.001	1.005	1.017	1.078
curvature	185	.785	.51	.018	.213	.731	.908	.935	.958	.966

In Iwanuma city, local government conducted metrical surveys and issued formal certificates for housing damage, with which households could obtain government compensation. During our experiments and in the main survey conducted in November 2013, we asked the participants about the level of housing damage. A cross tabulation of these damage levels is shown in Table 6.3 where ”today” refers to the data obtained in our experiments and ”half a year ago” refers to the data obtained from the main survey in November 2013. The different levels of damage are: totally collapsed or zenkai (5); almost collapsed or daikibohankai (4); half collapsed or hankai (3); minor damage or ichibu sonkai (2); or no damage (1). As shown in Table 6.4, we also collected data on subjective assessments of livelihood changes before and after the earthquake and tsunami, ranging from worsened (4); somewhat worsened (3); almost the same (2); and relatively improved (1).

Table 6.3: Today by half a year ago

	half_a_year_ago					
today	1	2	3	4	5	Total
1	19	0	0	0	0	19
2	2	13	2	0	0	17
3	0	3	17	1	0	21
4	1	0	3	50	25	79
5	0	0	0	7	41	48
Total	22	16	22	58	66	184

Source: Data in Iwanuma Experiment

Table 6.4: The Economic Condition

Item	Number	Per cent
1	3	2
2	113	62
3	48	26
4	18	10
Total	182	100

Source: Data in Iwanuma Experiment

To examine the impact of disasters, we re-estimate the CTB model allowing a heterogenous risk aversion parameter, α; time discounting parameter, δ; and present bias parameter, β, depending on the house damage level and livelihood change status. The results are presented in Table 6.5, where the subscript indicates the level of damage or change. Columns (1) and (2) allows heterogenous parameters based on house damage captured during the experiments and the main survey, respectively. Column (3) shows the results with heterogenous livelihood change impacts on the preference parameters. As we can see, the disaster affected the present bias parameter negatively. The disaster damage seems to make individuals slightly more present-biased, although, strictly speaking, the change caused by the disaster damage is not necessarily statistically significant.

Table 6.5: CTB results of Each Individual Group

	(1) *today*	(2) *half_a_year_ago*	(3) *economic_condition*
β_1	1.040***	1.039***	1.077***
	(0.0397)	(0.0299)	(0.0465)
β_2	1.018***	1.011***	1.039***
	(0.0252)	(0.0333)	(0.0212)
β_3	1.033***	0.993***	0.976***
	(0.0645)	(0.0452)	(0.0335)
β_4	0.960***	1.002***	0.898***
	(0.0539)	(0.0842)	(0.0811)
β_5	0.948***	0.955***	
	(0.0675)	(0.0549)	
δ_1	1.001***	1.000***	1.011***
	(0.00124)	(0.000886)	(0.00294)
δ_2	1.001***	1.001***	1.001***
	(0.000852)	(0.00122)	(0.000809)
δ_3	1.003***	1.004***	1.002***
	(0.00198)	(0.00167)	(0.00104)
δ_4	1.002***	1.003***	1.000***
	(0.00242)	(0.00188)	(0.00173)
δ_5	1.001***	1.000***	
	(0.00165)	(0.00153)	
α_1	0.888***	0.899***	0.820***
	(0.0140)	(0.0102)	(0.0439)
α_2	0.900***	0.890***	0.893***
	(0.00900)	(0.0125)	(0.00807)
α_3	0.878***	0.895***	0.909***
	(0.0223)	(0.0163)	(0.00950)
α_4	0.886***	0.845***	0.893***
	(0.0222)	(0.0291)	(0.0189)
α_5	0.914***	0.920***	
	(0.0111)	(0.00986)	
$\beta_1 = \cdots = \beta_5$	0.642	0.467	
$\beta_1 = \cdots = \beta_4$			0.101
$\delta_1 = \cdots = \delta_5$	0.818	0.314	
$\delta_1 = \cdots = \delta_4$			0.0075
$\alpha_1 = \cdots = \alpha_5$	0.467	0.078	
$\alpha_1 = \cdots = \alpha_4$			0.1870
N	4402	4450	4330

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2. Dictator Game Results

In addition to the CTB experiments, we conducted a dictator came experiment to elicit altruism. In the dictator game, the sender, called the "dictator," is provided with JPY 5,000 in 1,000 yen notes as the initial endowment that he/she can either keep or allocate to the receiver. Hence, the dictator must decide the transfer amount to his receiver from the possible transfer amounts of 0; 1,000; 2,000; 3,000; 4,000; or 5,000 yen. Since there is no self-interested reason for the sender to transfer money, the sender's zero transfers satisfy the Nash equilibrium. Hence, the actual positive amount of transfer is interpreted as the level of altruism (Camerer and Fehr, 2004; Levitt and List, 2009). We also adopt strategy methods, asking all participants as a sender the amounts they would send to each of three potential partners. Three partners are: a randomly selected person in the same residential area, a randomly selected victim of the Great East Japan Earthquake of March 2011, and a randomly selected person from Japan. Table 6.6 presents summary statistics of the amounts sent in the dictator games. We can see a substantial premium on altruism toward victims of the disaster in and outside Iwanuma city.

Table 6.6: Summary Statistics

Variable	Mean	Std. Dev.	N
donation_japan	1811.828	1244.26	186
donation_Iwanuma	2548.913	1120.011	184
donation_Earthquake	2792.35	1084.631	183

To investigate how the partner affects the subjects' responses and how damage suffered changes their responses, we postulate the following regression equation:

$$Donation_{ij} = \beta_0+\beta_1 Partner_{ij}+\beta_2 Damage_i+\beta_3 Partner_{ij}\times Damage_i+\beta_4 X_i+\epsilon_{ij} \tag{5}$$

where $Donation_{ij}$ is the amount the subject *i* gives to partner *j* in the dictator game, $Partner_{ij}$ is a dummy variable which indicates who is the partner, $Damage_i$ is a dummy variable which indicates whether the subject is affected by the disaster, X_{ij} is a control variable and ϵ_{ij} is an error term. We capture the damage by house damage described above.

Results without and with preference parameters are shown in Tables 6.7 and 6.8, respectively. While the amounts sent to victims of the Great East Japan Earthquake are larger than those sent to an anonymous person in Japan. The damage level, however, does not generate a clear pattern in terms of the sending amount. In Table 6.8, present bias parameter and time discount factor are both negatively related to the amount of donation, implying that seemingly altruistic behaviours might be based on myopia.

Table 6.7: The Relationship between the Amount of Donation and Earthquakes

	(1) donation	(2) donation	(3) donation
$today = 2$	-174.1		
	(568.2)		
$today = 3$	-443.0		
	(624.2)		
$today = 4$	-446.6		
	(532.8)		
$today = 5$	-451.8		
	(632.7)		
$Iwanuma$	428.6	400.0	1250.0*
	(514.3)	(370.4)	(568.1)
$Earthquake$	571.4	700.0^{+}	1750.0**
	(359.2)	(365.9)	(568.1)
$today = 2 \times Iwanuma$	-678.6		
	(538.9)		
$today = 2 \times Earthquake$	-571.4		
	(359.2)		
$today = 3 \times Iwanuma$	308.8		
	(620.6)		
$today = 3 \times Earthquake$	165.9		
	(497.8)		
$today = 4 \times Iwanuma$	285.7		
	(561.1)		
$today = 4 \times Earthquake$	722.9		
	(471.6)		
$today = 5 \times Iwanuma$	79.86		

	(563.9)		
$today = 5 \times Earthquake$	183.4		
	(470.0)		
$Date$	373.6	340.3	426.8
	(323.7)	(325.9)	(287.0)
$harf\_a\_year = 2$		166.0	
		(572.0)	
$harf\_a\_year = 3$		-375.2	
		(614.2)	
$harf\_a\_year = 4$		-131.5	
		(514.5)	
$harf\_a\_year = 5$		-65.71	
		(526.2)	
$harf\_a\_year = 2 \times Iwanuma$		-800.0^{+}	
		(436.2)	
$harf\_a\_year = 2 \times Earthquake$		-700.0^{+}	
		(365.9)	
$harf\_a\_year = 3 \times Iwanuma$		100.0	
		(494.7)	
$harf\_a\_year = 3 \times Earthquake$		-200.0	
		(491.3)	
$harf\_a\_year = 4 \times Iwanuma$		348.5	
		(472.2)	
$harf\_a\_year = 4 \times Earthquake$		875.8^{+}	
		(516.6)	
$harf\_a\_year = 5 \times Iwanuma$		155.2	
		(417.3)	

$harf\_a\_year = 5 \times Earthquake$		-65.19	
		(438.4)	
$condition = 2$			225.6
			(1116.6)
$condition = 3$			-214.6
			(1101.5)
$condition = 4$			-631.1
			(1261.8)
$condition = 2 \times Iwanuma$			-916.7
			(596.2)
$condition = 2 \times Earthquake$			-1000.0
			(622.8)
$condition = 3 \times Iwanuma$			-622.1
			(606.9)
$condition = 3 \times Earthquake$			-844.8
			(623.8)
$condition = 4 \times Iwanuma$			-1583.3*
			(635.0)
$condition = 4 \times Earthquake$			-1416.7*
			(635.0)
_cons	2018.9***	1761.8***	1679.9
	(516.4)	(471.8)	(1146.6)
N	185	185	185

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.8: The Relationship between the amount of Donation and Deep Parameters

	(1) donation	(2) donation	(3) donation
presentbias	-157.8*	-160.7**	-120.1+
	(62.77)	(59.87)	(62.47)
discountfactor	-14850.3***	-14942.1***	-13770.5***
	(2444.3)	(2349.4)	(3071.0)
curvature	-241.6	-136.2	-9.413
	(299.1)	(259.7)	(276.3)
$today = 2$	-93.16		
	(621.3)		
$today = 3$	-496.5		
	(671.4)		
$today = 4$	36.54		
	(592.0)		
$today = 5$	157.4		
	(636.8)		
$Iwanuma$	428.6	400.0	1250.0*
	(524.4)	(377.6)	(578.9)
$Earthquake$	571.4	700.0+	1750.0**
	(366.2)	(373.0)	(578.9)
$today = 2 \times Iwanuma$	-678.6		
	(549.5)		
$today = 2 \times Earthquake$	-571.4		
	(366.2)		
$today = 3 \times Iwanuma$	321.4		
	(687.5)		
$today = 3 \times Earthquake$	178.6		

	(576.0)		
$today = 4 \times Iwanuma$	312.2		
	(574.9)		
$today = 4 \times Earthquake$	724.9		
	(484.3)		
$today = 5 \times Iwanuma$	56.50		
	(575.8)		
$today = 5 \times Earthquake$	172.2		
	(482.9)		
$Date$	723.9*	608.8*	547.3^{+}
	(301.9)	(299.9)	(293.1)
gender	157.1	181.5	208.8
	(298.7)	(272.1)	(312.8)
age	788.6	867.6^{+}	657.1
	(477.8)	(504.2)	(470.4)
age2	-5.694^{+}	-6.164^{+}	-4.710
	(3.113)	(3.289)	(3.074)
$half\_a\_year = 2$		444.2	
		(566.0)	
$half\_a\_year = 3$		-10.57	
		(557.1)	
$half\_a\_year = 4$		362.4	
		(574.6)	
$half\_a\_year = 5$		413.1	
		(516.4)	
$half\_a\_year = 2 \times Iwanuma$		-800.0^{+}	
		(444.8)	

$half\_a\_year = 2 \times Earthquake$	-700.0^{+}	
	(373.0)	
$half\_a\_year = 3 \times Iwanuma$	100.00	
	(504.4)	
$half\_a\_year = 3 \times Earthquake$	-200.0	
	(501.0)	
$half\_a\_year = 4 \times Iwanuma$	389.5	
	(491.8)	
$half\_a\_year = 5 \times Earthquake$	878.9	
	(542.3)	
$half\_a\_year = 5 \times Iwanuma$	142.4	
	(426.3)	
$half\_a\_year = 5 \times Earthquake$	-73.09	
	(448.1)	
$condition = 2$		-26.66
		(1183.7)
$condition = 3$		-153.9
		(1121.5)
$condition = 4$		-77.74
		(1262.4)
$condition = 2 \times Iwanuma$		-916.7
		(607.6)
$condition = 2 \times Earthquake$		-1000.0
		(634.6)
$condition = 3 \times Iwanuma$		-601.6
		(622.2)
$condition = 3 \times Earthquake$		-837.8
		(640.2)

$condition = 4 \times Iwanuma$			-1583.3*
			(647.1)
$condition = 4 \times Earthquake$			-1416.7*
			(647.1)
_cons	-10242.1	-13711.3	-7092.7
	(18481.4)	(19337.2)	(18753.9)
N	182	182	182

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3. Behaviours

Existing studies in behavioural economics attribute undesirable behaviours such as obesity, over-eating, debt overhang, gambling, smoking, drinking, and other procrastination behaviours to naive hyperbolic discounting (Banerjee and Mullainathan, 2010). In our data, we can verify whether and how individual preferences are related to real-world decisions and other subjective responses. The estimation results are shown in Table 6.9, 6.10, and 6.11, and suggest an insignificant relationship between the present bias parameter and behaviours. The only exception is the level of residential- area specific general trust captured by the General Social Survey (GSS) type subjective assessment (column [P30 1] in Table 6.9). The coefficient is marginally significant. The qualitative result indicates that present bias coincides with a high level of trust between people in the same community, suggesting that present bias is closely related to bonding social capital within each community. Yet, it is not necessarily clear whether this observed relationship is driven by naive or sophisticated hyperbolic discounting.

Table 6.9: The Relationship between Questions and Deep Parameters (Orders Probit)

	(1) P30 1)	(2) P30 2)	(3) P30 3)	(4) P31 1)	(5) P31 2)	(6) P31 3)	(7) P32 1)
main							
presentbias	0.0897	-0.0567	0.0319	-0.102	-0.0160	-0.0509	-0.0244
	(0.0562)	(0.0635)	(0.0595)	(0.0828)	(0.0427)	(0.0467)	(0.0433)
discountfactor	1.199	1.620	-4.211^{+}	2.347	0.703	3.486	1.718
	(2.447)	(2.959)	(2.303)	(3.152)	(2.351)	(2.630)	(2.558)
curvature	0.0645	0.386	0.185	-0.117	-0.219	0.00244	-0.0704
	(0.280)	(0.266)	(0.263)	(0.222)	(0.180)	(0.238)	(0.198)
gender	0.390*	-0.200	-0.0255	-0.0395	-0.483**	-0.272^{+}	-0.821***
	(0.184)	(0.173)	(0.173)	(0.164)	(0.164)	(0.165)	(0.169)
age	-0.0203	-0.0620	-0.139	-0.117	-0.696*	-0.244	0.0149
	(0.350)	(0.359)	(0.316)	(0.286)	(0.304)	(0.260)	(0.216)
age2	-0.0000078	0.00022	0.00073	0.00071	0.0046*	0.0016	-0.00015
	(0.0023)	(0.0024)	(0.0021)	(0.0019)	(0.0020)	(0.0017)	(0.0014)
cut1							
_cons	-1.203	-2.838	-10.89	-4.552	-27.65*	-7.639	0.611
	(13.66)	(13.95)	(12.28)	(11.49)	(11.58)	(10.18)	(8.816)
cut2							
_cons	0.956	-1.128	-9.388	-4.002	-26.68*	-6.768	1.435
	(13.65)	(13.95)	(12.28)	(11.49)	(11.57)	(10.16)	(8.810)
cut3							
_cons	2.012	-0.261	-8.704	-3.565	-26.26*	-6.482	1.912
	(13.67)	(13.95)	(12.25)	(11.50)	(11.57)	(10.16)	(8.811)
cut4							
_cons	2.380	1.061	-7.687	-3.055	-25.85*	-5.614	2.733
	(13.71)	(14.11)	(12.25)	(11.50)	(11.57)	(10.15)	(8.808)
cut5							
_cons				-2.259	-25.58*	-5.221	3.443
				(11.50)	(11.57)	(10.14)	(8.807)
N	178	178	178	170	174	174	177

Standard errors in parentheses

Standard errors in parentheses : $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.10: The Relationship between Questions and Deep Parameters (continued)(Orders Probit)

	(1) P32 2)	(2) P34 1)	(3) P34 2)	(4) P34 3)	(5) P35 1)	(6) P36 2)
main						
presentbias	0.0972	-0.0141	0.0870	0.106	0.0747	0.0152
	(0.0844)	(0.0802)	(0.0965)	(0.0791)	(0.0919)	(0.0592)
discountfactor	2.090	3.296	-3.541	-3.987	-1.340	-3.597
	(3.182)	(3.601)	(2.853)	(3.645)	(2.585)	(2.457)
curvature	0.128	-0.100	-0.407	-0.147	-0.109	0.0485
	(0.225)	(0.318)	(0.316)	(0.300)	(0.257)	(0.357)
gender	0.648***	0.202	0.363+	0.0572	-0.323+	0.230
	(0.184)	(0.194)	(0.201)	(0.200)	(0.186)	(0.183)
age	0.592+	-0.373	0.0649	-0.0771	0.00275	0.759*
	(0.319)	(0.360)	(0.350)	(0.360)	(0.366)	(0.351)
age2	-0.00390+	0.00259	-0.0000103	0.000427	-0.0000460	-0.00523*
	(0.00212)	(0.00240)	(0.00235)	(0.00239)	(0.00243)	(0.00233)
_cons				7.776		
				(14.04)		
cut1						
_cons	23.09	-11.28	-1.021		-3.171	21.95
	(12.36)	(13.92)	(12.78)		(13.92)	(13.40)
cut2						
_cons	23.55	-10.49	0.631		-1.117	22.90
	(12.37)	(13.93)	(12.83)		(13.92)	(13.36)
cut3						
_cons	24.55*					25.13
	(12.40)					(13.37)
cut4						
_cons	25.04*					26.16
	(12.41)					(13.38)
N	179	175	177	175	176	179

Standard errors in parentheses

Standard errors in parentheses : $^{+}$ p < 0.10, * p <0.05, ** p<0.01, *** p< 0.001

6. Concluding Remarks

Several important findings emerge from our study. First, we found that we cannot reject the null hypothesis in which the estimated present bias parameter equals one, indicating the absence of quasi-hyperbolic discounting in the whole sample. The estimated time discount rate is close to zero and the estimated risk aversion parameter is within a reasonable range. Overall, we can safely say that the subjects drawn from Iwanuma city are forward-looking and patient and without tendencies of quasi-hyperbolic discounting. Yet, the estimated individual-level preference parameters show that, while discount factor and risk parameters are clustered, there are large variations in the present bias and risk preference parameters. Secondly, we found that the disaster affected the present bias parameter negatively. The disaster damage seems to have made individuals more present-biased. Third, in dictator games, the amounts sent to victims of the Great East Japan Earthquake are larger than those sent to arbitrary persons in Japan. The damage level, however, does not generate a clear pattern in terms of the sending amount. Also, we found that present bias parameter and time discount factor are both negatively related to the amount of donation, implying that seemingly altruistic behaviours might be driven by myopic preference.

Since existing studies attribute undesirable behaviours such as obesity, over-eating, debt overhang, gambling, smoking, drinking, and other procrastination behaviours to naive hyperbolic discounting (Banerjee and Mullainathan, 2010), in our data, we investigate whether and how individual preferences are related to real-world decisions and other subjective responses. According to our estimation results, relationships between the present bias parameter and behaviours are largely insignificant statistically. The only exception is the level of residential area-specific general trust captured by the General Social Survey (GSS) type subjective assessment questions. This result implies that present bias coincides with a high level of trusting people within the same community, suggesting that present bias is closely related to bonding social capital within each community. However, it is not necessarily clear that this revealed relationship is driven by naive or sophisticated hyperbolic discounting. To verify the internal and external validity of the findings presented in this paper, future studies to examine the impact of disasters on individual and social preferences will be needed.

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Appendix

Figure 6.A.1: The Histogram of the Damage

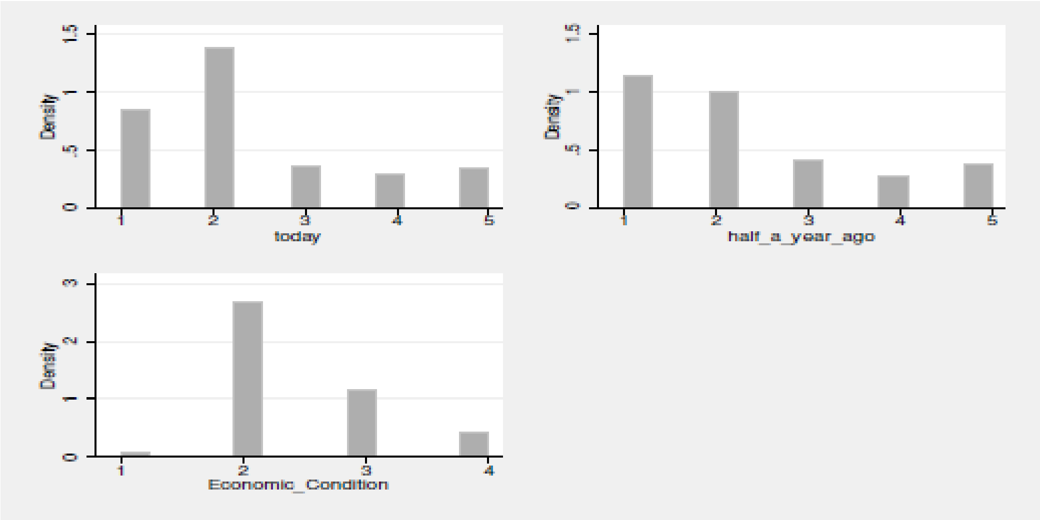

Figure 6.A.2: The Histogram of the Amount of Donation

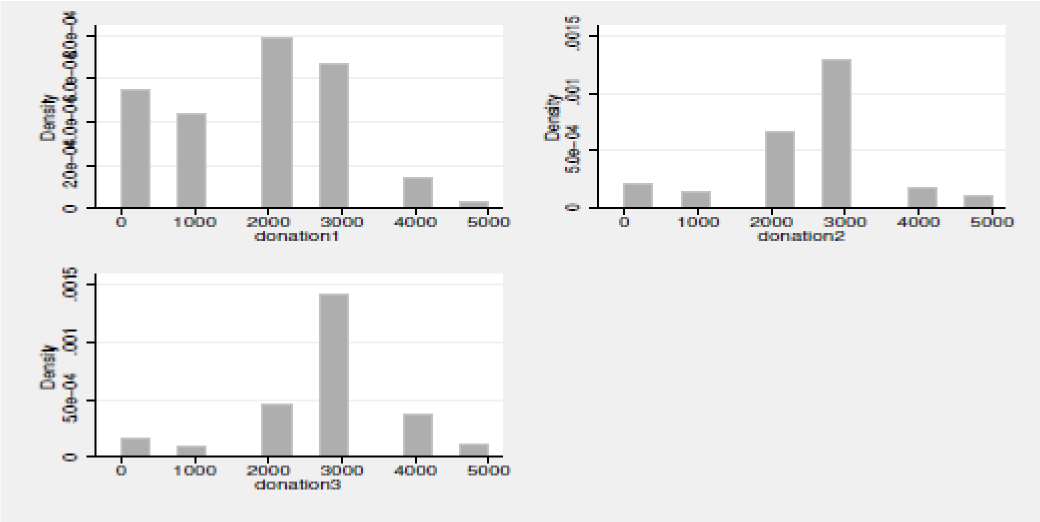

Figure 6.A.3: The Cumulative Distribution Function (CDF) of Present-bias with Respect to Today's Damage

cum1 ⋯ no change, cum2 ⋯ minor damage, cum3 ⋯ partial damage, cum4 ⋯ partial damage in a large scale, cum5 ⋯ complete damage

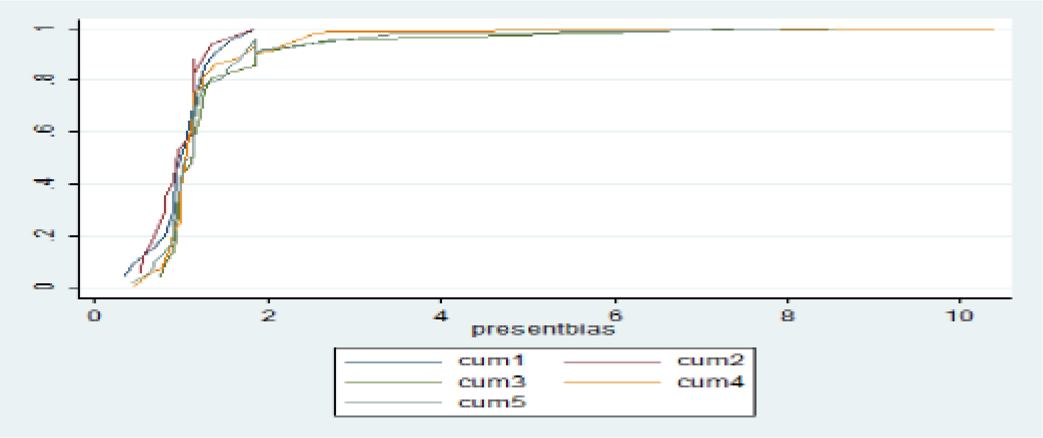

Figure 6.A.4: The CDF of Discount Factor with Respect to Today's Damage

cum1 ⋯ no change, cum2 ⋯ minor damage, cum3 ⋯ partial damage, cum4 ⋯ partial damage in a large scale, cum5 ⋯ complete damage

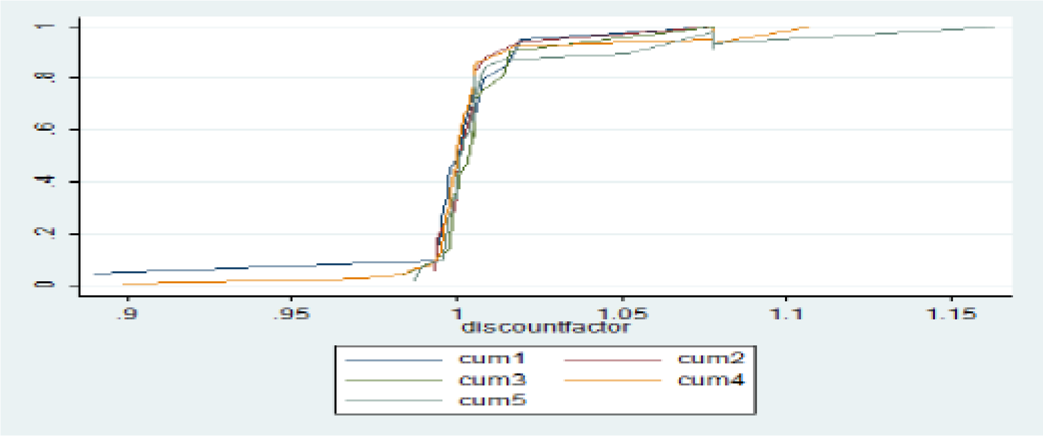

Figure 6.A.5: The CDF of Curvature with Respect to Today's Damage

cum1 ⋯ no change, cum2 ⋯ minor damage, cum3 ⋯ partial damage, cum4 ⋯ partial damage in a large scale, cum5 ⋯ complete damage

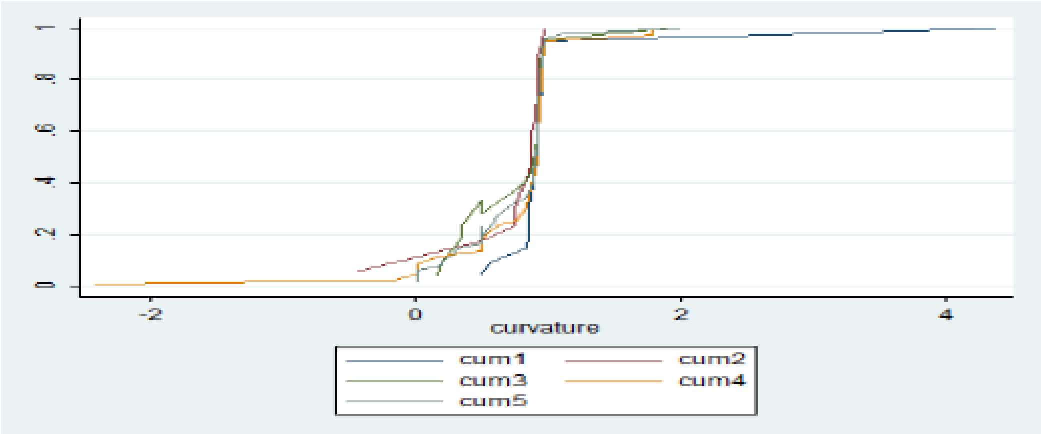

Figure 6.A.6: The CDF of Present-bias with Respect to half a year ago's Damage

cum1 ⋯ no change, cum2 ⋯ minor damage, cum3 ⋯ partial damage, cum4 ⋯ partial damage in a large scale, cum5 ⋯ complete damage

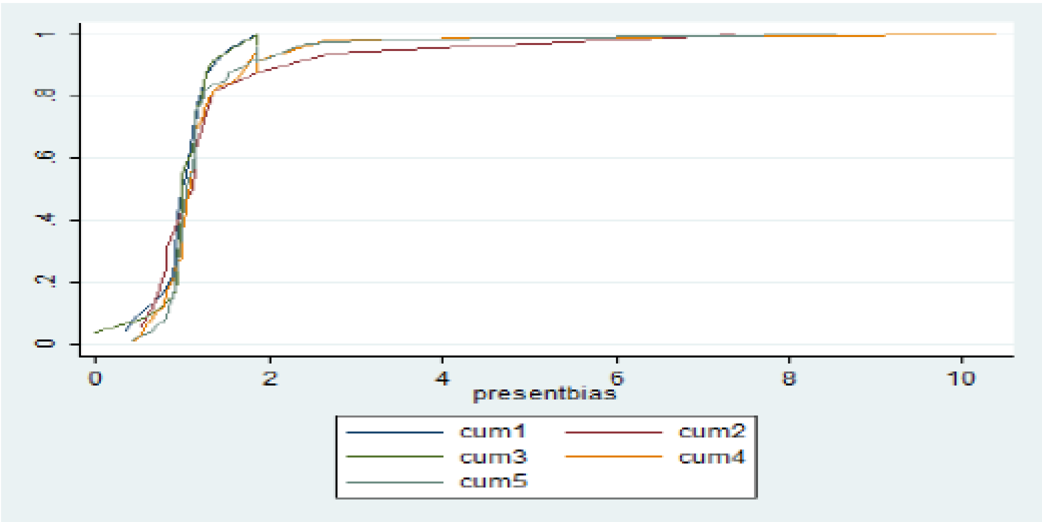

Figure 6.A.7: The CDF of Discount Factor with Respect to half a year ago's Damage

cum1 ⋯ no change, cum2 ⋯ minor damage, cum3 ⋯ partial damage, cum4 ⋯ partial damage in a large scale, cum5 ⋯ complete damage

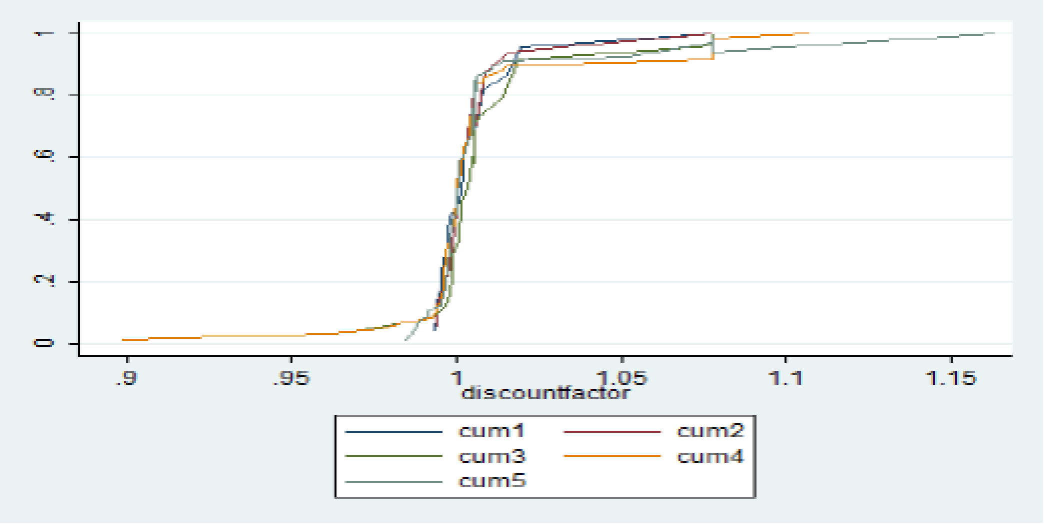

Figure 6.A.8: The CDF of Culvature with Respect to half a year ago's Damage

cum1 ⋯ no change, cum2 ⋯ minor damage, cum3 ⋯ partial damage, cum4 ⋯ partial damage in a large scale, cum5 ⋯ complete damage

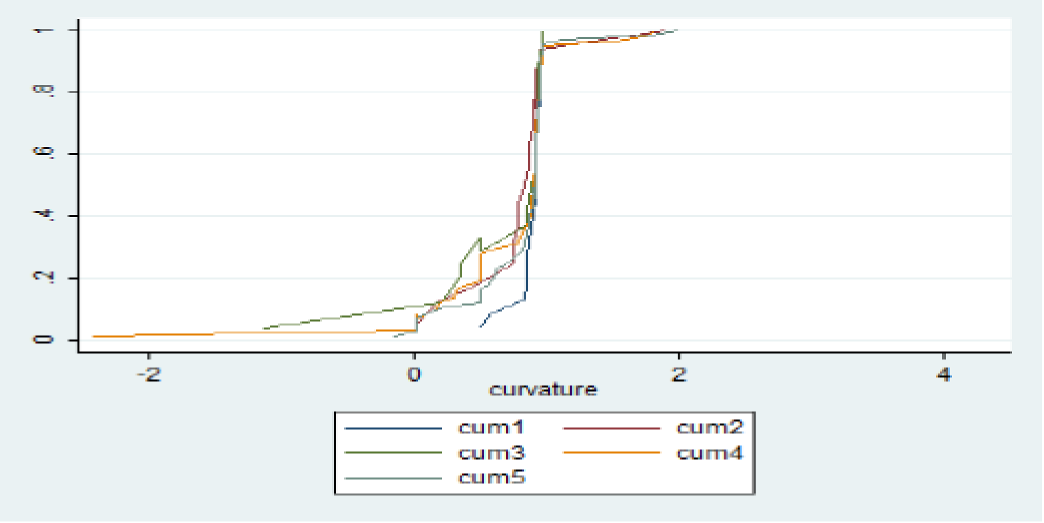

Figure 6.A.9: The CDF of Present-bias with Respect to Today's Economic Condition

cum1 ⋯ a little well, cum2 ⋯ no change, cum3 ⋯ a little bad, cum4 ⋯ bad

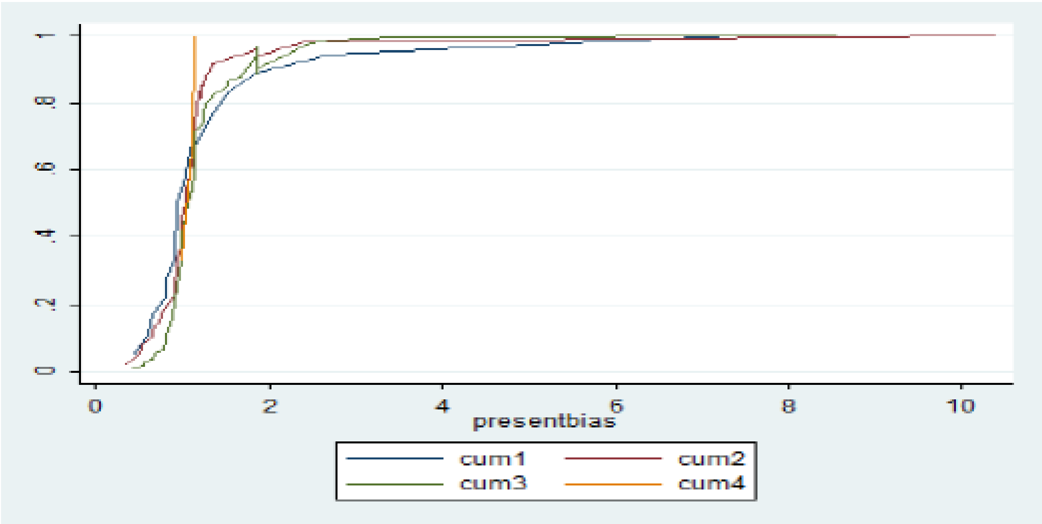

Figure 6.A.10: The CDF of Discount Factor with Respect to Today's Economic Condition

cum1 ⋯ a little well, cum2 ⋯ no change, cum3 ⋯ a little bad, cum4 ⋯ bad

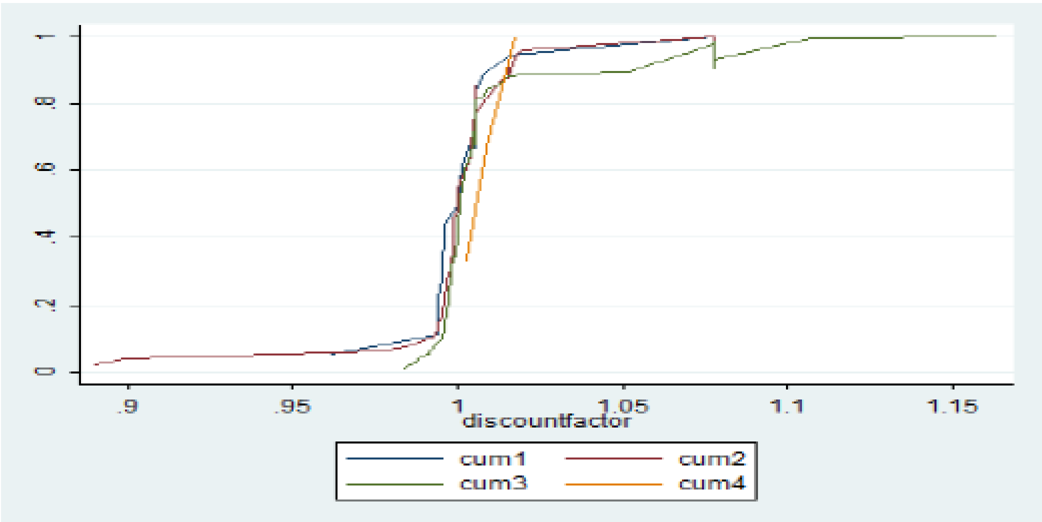

Figure 6.A.11: The CDF of Culvature with Respect to Today's Economic Condition

cum1 $\cdots$ a little well, cum2 $\cdots$ no change, cum3 $\cdots$ a little bad, cum4 $\cdots$ bad

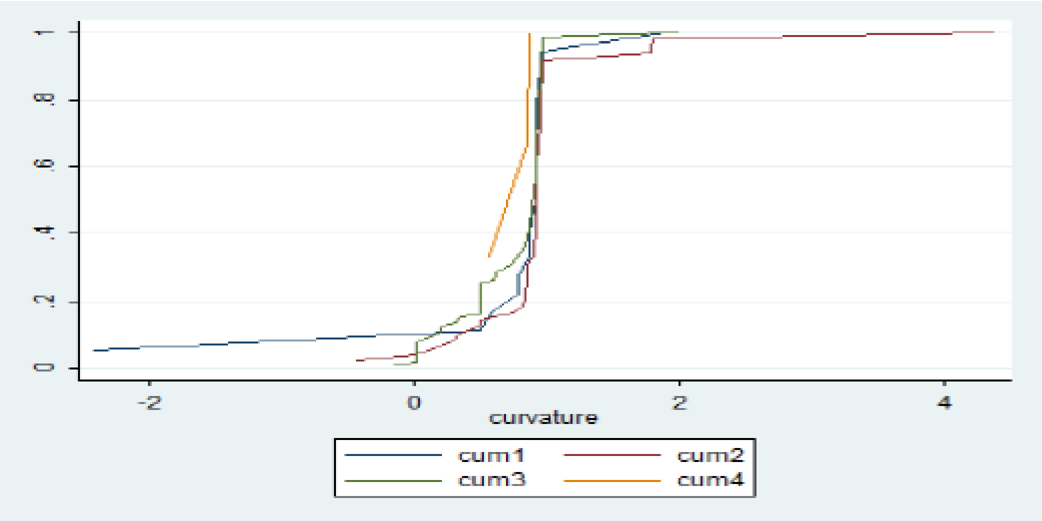

Table 6.A.1: The Relationship between Question and Deep Parameters (Linear Regression)

	(1) P30 1)	(2) P30 2)	(3) P30 3)	(4) P31 1)	(5) P31 2)	(6) P31 3)	(7) P32 1)
presentbias	0.0334	-0.0424	0.0120	-0.168	-0.0213	-0.0811	-0.0378
	(0.0296)	(0.0431)	(0.0470)	(0.133)	(0.0726)	(0.0741)	(0.0569)
discountfactor	0.233	1.340	-3.258*	2.971	2.255	5.060	3.080
	(1.307)	(2.318)	(1.499)	(3.900)	(3.672)	(3.745)	(3.322)
curvature	0.0413	0.307+	0.131	-0.0793	-0.418	-0.00609	-0.116
	(0.138)	(0.180)	(0.181)	(0.272)	(0.281)	(0.342)	(0.255)
gender	0.188+	-0.155	-0.0628	-0.193	-0.784**	-0.430+	-1.036***
	(0.0977)	(0.128)	(0.132)	(0.206)	(0.251)	(0.230)	(0.207)
age	-0.0827	-0.0597	-0.128	-0.102	-1.091*	-0.434	0.0865
	(0.224)	(0.267)	(0.234)	(0.369)	(0.431)	(0.394)	(0.289)
age2	0.000470	0.000264	0.000714	0.000592	0.00719*	0.00286	-0.000651
	(0.00146)	(0.00176)	(0.00154)	(0.00243)	(0.00283)	(0.00260)	(0.00188)
_cons	5.234	3.832	10.74	6.385	43.80**	15.71	-2.424
	(8.804)	(10.49)	(9.033)	(14.39)	(16.51)	(15.12)	(11.84)
N	178	178	178	170	174	174	177

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.A.2: The Relationship between Question and Deep Parameters (continued) (Linear Regression)

	(1)	(2)	(3)	(4)	(5)	(6)
	P32 2)	P34 1)	P34 2)	P34 3)	P35 1)	P36 2)
presentbias	0.0850	-0.00958	0.0258	0.0264	0.0325	-0.000539
	(0.0632)	(0.0506)	(0.0235)	(0.0184)	(0.0399)	(0.0343)
discountfactor	1.961	1.699	-1.282	-1.320	-0.636	-1.542
	(2.500)	(1.835)	(1.201)	(1.307)	(1.195)	(1.330)
curvature	0.118	-0.0210	-0.151	-0.0517	-0.0472	0.0598
	(0.225)	(0.183)	(0.114)	(0.105)	(0.124)	(0.221)
gender	0.614***	0.104	0.141+	0.0214	-0.156+	0.102
	(0.170)	(0.106)	(0.0790)	(0.0734)	(0.0869)	(0.0989)
age	0.566+	-0.159	0.0992	-0.0289	0.000888	0.446*
	(0.308)	(0.161)	(0.120)	(0.127)	(0.176)	(0.215)
age2	-0.00371+	0.00111	-0.000509	0.000161	-0.0000176	-0.00306*
	(0.00205)	(0.00105)	(0.000786)	(0.000848)	(0.00117)	(0.00143)
_cons	-19.89+	6.496	-0.565	3.243	2.024	-11.73
	(11.81)	(6.566)	(4.670)	(5.040)	(6.694)	(8.123)
N	179	175	177	175	176	179

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.A.3: The Relationship between the Amount of Public Money and the Number of Neighborhood

	(1) publicmoney	(2) publicmoney
group = 1	206.4**	209.7**
	(77.83)	(78.10)
neighbourhood = 1	-220.4	-205.9
	(207.3)	(205.2)
neighbourhood = 2	518.3	576.3
	(483.3)	(486.7)
neighbourhood = 3	139.4	97.87
	(146.9)	(170.4)
neighbourhood = 4	-1762.7***	-1675.2***
	(304.4)	(322.1)
age	-608.9+	-541.2
	(340.4)	(338.5)
age2	3.891+	3.446
	(2.258)	(2.247)
gender	-289.5	-296.0
	(181.2)	(183.8)
presentbias		105.9*
		(46.27)
discountfactor		5293.1
		(3464.9)
curvature		-19.74
		(228.7)
_cons	26587.8*	18590.1
	(12782.2)	(13446.8)
N	355	351

Standard errors in parentheses : $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.A.4: The Relationship between the Amount of Public Money, the Number of Neighborhood and the Amount of Donation

	(1)	(2)
	publicmoney	publicmoney
$group = 1$	196.8*	197.4*
	(78.52)	(78.77)
$neighbourhood = 1$	-229.1	-217.8
	(198.9)	(193.9)
$neighbourhood = 2$	745.2	838.3^{+}
	(465.9)	(484.8)
$neighbourhood = 3$	35.18	36.54
	(196.1)	(220.8)
$neighbourhood = 4$	-952.5*	-851.9^{+}
	(474.4)	(475.4)
$dictator = 1000$	-612.3	-727.7^{+}
	(429.9)	(422.1)
$dictator = 2000$	-448.1	-481.3
	(386.4)	(385.0)
$dictator = 3000$	-682.8^{+}	-648.2^{+}
	(360.2)	(357.3)
$dictator = 4000$	-1392.6**	-1370.2**
	(522.4)	(518.9)
$dictator = 5000$	-1050.3	-827.1
	(1022.4)	(1307.1)
age	-536.0	-456.1
	(336.3)	(320.9)
age2	3.352	2.813
	(2.233)	(2.130)
gender	-206.7	-197.2
	(184.5)	(192.2)
presentbias		117.6*
		(54.23)
discountfactor		4336.1
		(3190.9)
curvature		34.38
		(205.5)
_cons	24723.9*	17221.9
	(12522.8)	(12290.9)
N	353	349

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.A.5: Tabulations of Responses to Hypothetical Time Preference Questions

Indifferent between 20000 yen now and X in one months	Indifferent between 20000 yen in 6 months and X in 7 months Patient $X < 25000$	Somewhat Patient $25000 < X < 30000$	Most impatient $30000 < X$	Total
Patient	125	11	1	137
$X < 25000$	69.44 %	6.11 %	0.56 %	76.11 %
Somewhat Patient	9	12	5	26
$25000 < X < 30000$	5.00 %	6.67 %	2.78 %	14.44 %
Most impatient	2	5	10	17
$30000 < X$	1.11 %	2.78 %	5.56 %	9.44 %
Total	136	28	16	180
	75.56 %	15.56 %	8.89 %	100 %

Source: data1521.dta

Table 6.A.6: The Relationship between Subjective Hyperbolic Discounting and the Severity of the Damage

	(1) hyperbolic	(2) hyperbolic	(3) hyperbolic
$today = 2$	0.00619		0.0120
	(0.0524)		(0.0560)
$today = 3$	-0.0906*		-0.0822^{+}
	(0.0439)		(0.0496)
$today = 4$	0.0856		0.112
	(0.104)		(0.113)
$today = 5$	-0.0333		0.00771
	(0.0710)		(0.0897)
age	-0.0336	-0.0263	-0.0444
	(0.0677)	(0.0620)	(0.0669)
age2	0.000219	0.000175	0.000301
	(0.000439)	(0.000400)	(0.000434)
gender	0.00747	0.0256	0.0148
	(0.0478)	(0.0425)	(0.0470)
$condition = 2$		0.124*	0.173*
		(0.0545)	(0.0735)
$condition = 3$		0.0999	0.143^{+}
		(0.0616)	(0.0762)
$condition = 4$		0.0217	0.0639
		(0.0388)	(0.0644)
_cons	1.362	0.942	1.547
	(2.617)	(2.416)	(2.585)
N	180	178	178

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.A.7: The Relationship between Subjective Hyperbolic Discounting and Temporary Residence

	(1) hyperbolic
temporary	0.0876
	(0.0926)
$today = 2$	0.00977
	(0.0561)
$today = 3$	-0.0930^{+}
	(0.0511)
$today = 4$	0.0969
	(0.109)
$today = 5$	-0.0638
	(0.105)
$condition = 2$	0.171*
	(0.0726)
$condition = 3$	0.144^{+}
	(0.0755)
$condition = 4$	0.0747
	(0.0629)
age	-0.0464
	(0.0671)
age2	0.000314
	(0.000436)
gender	0.0220
	(0.0457)
_cons	1.615
	(2.593)
N	178

Standard errors in parentheses : $^{+}$ p < 0.10, * p <0.05, ** p<0.01, *** p< 0.001

Table 6.A.8: The Relationship between Present-bias and Temporary Residence

	(1)	(2)
	presentbias	presentbias
temporary	-0.242*	-0.225
	(0.112)	(0.140)
age	-0.538	-0.511
	(0.606)	(0.559)
age2	0.00370	0.00355
	(0.00413)	(0.00383)
gender	-0.205	-0.175
	(0.163)	(0.204)
$today = 2$		-0.160
		(0.210)
$today = 3$		0.0908
		(0.258)
$today = 4$		-0.288
		(0.196)
$today = 5$		-0.193
		(0.229)
$condition = 2$		0.369
		(0.476)
$condition = 3$		0.494
		(0.586)
$condition = 4$		0.595
		(0.716)
_cons	20.80	19.36
	(22.09)	(19.97)
N	180	176

Standard errors in parentheses

Standard errors in parentheses : $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

CHAPTER 7
Natural Disaster and Human Capital Accumulation: The Case of the Great Sichuan Earthquake in China*

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In this paper, we employ original micro data collected from students and schools affected by the Great Sichuan Earthquake in 2008 to uncover the impacts of the earthquake on the broad human capital of students, i.e., their cognitive and non-cognitive outcomes. Two main findings emerge from our empirical analysis. First, the household-level shocks due to the earthquake worsen a child's psychosocial outcomes as well as family environment uniformly. Second, classroom relocations due to the earthquake mitigate depression, enhance self-esteem, improve family environment, and improve Chinese test scores. These effects may reflect positive peer effects through the earthquake-affected students' unexpected exposure to students and facilities in better schools. Since non-cognitive skills may be more malleable than cognitive skills at later ages, the government must play an important role in facilitating human capital accumulation in a broader sense effectively by amending the non-cognitive skills of children affected by a natural disaster directly or indirectly.

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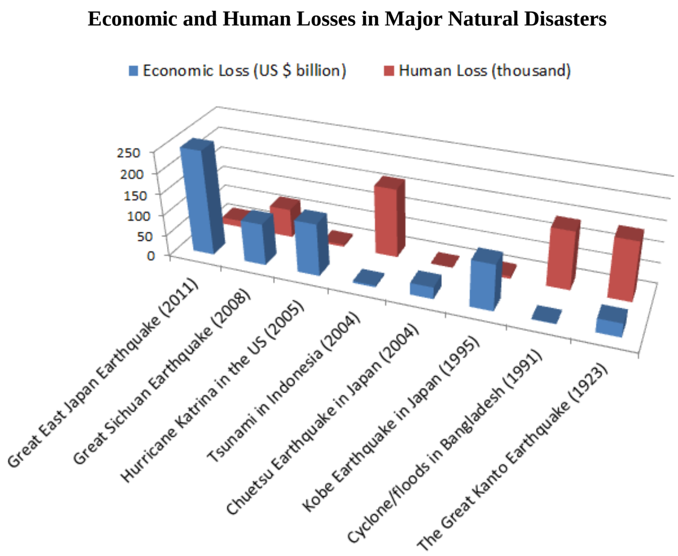
1. Introduction

On the afternoon of May 12th, 2008, Wenchuan County of China's Sichuan Province was hit by a devastating earthquake measuring 7.9 on the Richter scale (USGS, 2012). The epicentre of the earthquake was 80 kilometers from Chengdu, the capital of Sichuan, home to more than 14 million people. The earthquake resulted in confirmed losses of more than 69,000 lives and economic losses exceeding RMB 845 billion. As can be seen in Figure 7.1, the scale of the losses means that the earthquake is one of the largest economic disasters ever recorded in human history (Park and Wang, 2012; Sawada, 2013). Yet, there are only few studies that document how the earthquake affected individual households in the disaster-affected areas (Park and Wang, 2009, 2012; Shi *et al*., 2012; Huang *et al*., 2011). Particularly, it is largely unknown how such a traumatic shock affects the psychosocial situations as well as cognitive achievements of children in schools.

Figure 7.1: Economic and Human Losses in Major Natural Disasters



Source: Sawada (2007), USGS (2012), and Cabinet Office (2011).

The purpose of this paper is to bridge this gap in the literature. We explore the exogenous variations in earthquake outbreak and students' relocations to uncover the psychosocial as well as cognitive impacts of earthquakes on children. In addition to surveys in Wenchuan County, we study Mao County, a nearby county with a lower level of damage, to identify the causal impacts of the earthquake. Right after the earthquake, all the schools in Wenchuan County and the surrounding areas were closed, with no exams given for the semester. In July 2008, the Wenchuan County education bureau decided to send all the students to other places to continue their studies. By August 2008, most of the students had been relocated to other cities or counties not seriously affected by the Sichuan earthquake as well as other provinces including Guangdong, Shanxi, Shandong, Beijing, and Fujian. In January 2009, the schools had their own exams for the fall semester, and in July 2009, the school year end exams were organised for all the students by the county education bureau. After the school year end exams were over in late July 2009, the students returned to Wenchuan County. In September 2009, the students started their studies in their new schools in Wenchuan County.

Using this unique natural experimental situation, we study how the experience of being temporarily relocated to new schools after the earthquake influenced the educational and life outcomes of students from Wenchuan County. Most of the middle school and high school students in Wenchuan County were relocated to schools in the Guangdong, Shanxi, or other regions of Sichuan. The preliminary results from the analysis of students and school survey data show that many parents felt that the school environment and grade attainment of their children improved after the temporary relocation to new schools (Park and Wang, 2009). This suggests that such temporary relocation may have played a positive role in the students' development, perhaps through the better environmental factors or positive peer effects resulting from the interaction of students, teachers, and principals with their counterparts in the host schools in more developed regions. In addition, the randomness in the assignment of schools to different host schools creates an exogenous variation in the quality of the host schools, providing an unusual research opportunity to evaluate how the different aspects of the relocation experience and characteristics of the host schools influence the development of students. Using carefully organised student-, teacher-, and school-level surveys, we examine the impacts of the earthquake. The results of the study will have valuable implications for designing public intervention policies to rehabilitate children during educational as well as psychological problems caused by natural disasters.

This paper is organised as follows: The next section reviews the existing studies on the impacts of natural disasters. In the third section, we describe our research design for the school surveys in Sichuan province, followed by data description in the fourth section. The fifth section gives the econometric framework and estimation results, followed by our concluding remarks in the final section.

2. Literature Review

A major natural disaster causes the immediate loss of hundreds of thousands of lives, and it has been found that hydro-meteorological natural disasters such as cyclones, floods, and droughts are increasing in number (e.g., Cavallo and Noy, 2009; Kellenberg and Mobarak, 2011; Strömberg, 2007). Both the developed and developing countries are continuing to be hit by high-profile natural disasters such as the 2011 devastating earthquake, tsunami, and nuclear radiation crisis in Japan; the Indian Ocean tsunami; Hurricane Katrina; and earthquakes in central Chile, Haiti, the Sichuan province of China, northern Pakistan, and the Hanshin area of Japan. These natural disasters not only cause the loss of human lives but also destroy the survivors' livelihoods. It is known that the poor in the developing countries are particularly vulnerable to natural disasters (World Bank and United Nations, 2010).

While there are a number of studies on the macroeconomic impacts of natural disasters (for example, Kahn, 2005; Freeman *et al*., 2003; Noy, 2009; Barro, 2009; Strömberg, 2007; Skidmore and Toya, 2007; Raddaz, 2007; and Yang, 2008), there are relatively few microeconomic studies (Kunreuther *et al*., 1978; Carter *et al*., 2007; Skoufias, 2003; Morris and Wodon, 2003; Kohara *et al*., 2006; Gitter and Barham, 2007; Sawada, 2007; Sawada, *et al*., 2009; de Mel *et al*., 2012; Halliday, 2006, 2012; Frankenberg *et al*., 2008; Nakata *et al*., 2010; Frankenberg *et al*., 2011; Shoji, 2010; Takasaki, 2011; Sawada, 2013). These micro studies examine the individual- or household-level ex post facto coping strategies against disasters, because disasters happen unexpectedly, causing serious negative impacts on household welfare. Since the formal insurance mechanisms against losses caused by natural disasters are weak

(Cummins, 2006), most individuals often adopt inappropriate responses against natural disasters, often sacrificing physical and/or human capital investments. Sawada (2013) and Sawada and Shimizutani (2008, 2011) show that credit market access plays an important role in weathering the damage caused by disasters in developed countries. Yet, the poor in the developing counties are likely to be excluded from effective credit access to cope with damage caused by natural disasters. Theoretically, under binding borrowing constraints, a household has an incentive to reallocate its resources intertemporally to cope with unexpected negative shocks by cutting back on physical and human capital investments.

Of course, there are several studies based on micro data from developing countries focusing on the impacts of exogenous shocks on human capital investments (Jacoby and Skoufious, 1997; Garg and Morduch, 1998; Jensen, 2000; Thomas *et al*., 2004; Beegle *et al*., 2006; Fitzsimons, 2007; Sawada and Lokshin, 2009; Duryea *et al*., 2007). For example, Foster (1995) found that the negative income shocks due to price shocks translate into the low growth of children under credit market imperfections. Moreover, Kochar (1999) found that such negative shocks increase the labour force participation of parents. Behrman (1988) found that the nutrition of girls is affected more than that of boys in the lean season. Similarly, Behrman and Deolalikar (1988) reported that price changes affect the consumption level of girls more than that of boys. As a consequence, Rose (1999) found that girls suffer disproportionately from adverse shocks, evaluated by mortality rate. Using micro data from Ethiopia, Dercon and Krishnan (2000) found that women in these households, who engage in risk-sharing, bear the brunt of adverse shocks, while examining the ability of individual members of households to keep the consumption smooth over time. Using a Pakistan panel data set, Alderman and Gertler (1997) found that the income elasticities of demand for medical expenditure are uniformly larger for females than for males.

Yet, these existing studies investigate the usual exogenous income shocks, and almost no paper exists that investigates how extreme shocks arising from natural disasters affect human capital investments. This paper tries to bridge this gap in the literature by examining the impacts of the Great Sichuan Earthquake on the cognitive and non-cognitive outcomes of children affected by the earthquake.

3. Research Design

As part of the *Kin Mirai Kadai Kaiketsu Jigyo* project of the Hitotsubashi University, headed by Professor Makoto Saito, we conducted our study in the Wenchuan County as well as the Mao County, a nearby county with a lower level of damage, in December 2009. We conducted our study of primary schools, middle schools, and high schools in Wenchuan County and middle schools and high schools in Mao County. To be more precise, the following four types of respondent groups are included in our study:

First, the "(present) schools," that is, the schools existing when the research was carried out. The headmaster or a staff member who knows well the overall affairs of the researched school (A) is required to fill in the forms. Each school submits one set of the "Questionnaire for (present) schools" forms.

Second, the "schools before the earthquake," that is, all the schools that existed before the earthquake. A staff member who knows well the overall affairs of the former schools is required to fill in the forms. If school (A) includes students from three former schools B1, B2, and B3, the situation about all the three former schools needs to be submitted in separate forms. Hence, there will be three sets of the "Questionnaire for schools before the earthquake" forms.

Third, all the teachers in charge of any subject in the researched schools are required to fill in the forms. Specifically, the teachers in charge of the lectures from Grade 3 to Grade 6 in the targeted primary schools need to fill in the forms, while with regard to middle schools and high schools, all the teachers in charge of the subjects of all the grades need to fill in the forms. Each teacher submits one set of the "Questionnaire for teachers" forms.

Finally, all the students in the selected classes are required to fill in the forms. Each student submits one set of the "Questionnaire for students" forms.

With the financial support from the Economic Research Institute for ASEAN and East Asia (ERIA), the research team updated our original microdata collected from students and schools affected by the great Sichuan earthquake in 2009. We collected high school entrance exam record for all middle school students and college entrance exam record for all high school students we surveyed in 2009. All the new data collection was done in March 2014. Using this unique natural experimental situation tracked by our unique surveys, this research will study how the experience of being exposed to the earthquake affects human capital accumulation.

3.1. Sampling Procedure

The school sample for the research on education in earthquake-hit areas includes all the primary schools, middle schools, and high schools in Wenchuan County, except for the special children educational schools and schools in the Wolong Special District, as well as the middle schools and high schools in Mao County. All the schools in the sample are required to fill in the school questionnaires. From the school samples, all the teachers in charge of subjects from Grade 3 to Grade 6 in primary schools and any subject in the middle schools and high schools are included in our teacher samples. As for the student survey, the most important component of this study, the sampling object is selected from every school of the sample: 50% of all the classes in each grade are randomly selected. All the students in the selected classes comprise the student samples. The sampling approach we adopt to select the target classes is the "Simple Equidistant Random Sampling" method.[1] Using this method, we sample each grade in each school to select the classes. All the students in each selected class are students in the sample.

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[1] Specifically, (1) arrange all the classes from Class 1 to Class n in Grade G with the number of students in each class; (2) multiply the total number of students in Grade G with a random number to get the product, say 98; (3) from the cumulative number of students in the classes, check which class the 98th student belongs to. If the student belongs to Class C, Class C is the first class selected in Grade G; (4) because 50% of the classes in each grade are selected, meaning that the distance between the neighboring classes in the sample is 2, using Class C, add or subtract the distance to get the other classes into the sample.

3.2. Survey Implementation

Our field surveys are conducted by three professors from the Renmin University of China and the Sichuan University, as leaders, and 18 PhD and MA students from the two universities. Before the field research, a training session was conducted on December 5th, 2009. The staff members in charge of the project gave training to all the investigators. The main issues included, first, training on the contents of the questionnaires for students, teachers, and schools in order to enable the investigators answer the questions that arise when actually having to fill in the questionnaires and second, training on how to guide the process of investigation in order to assist the investigators arrange a reasonable investigation process, control the speed, and avoid flaws.

The field research was conducted from December 6 to December 10, 2009. All the members were divided into two groups to carry out the research in Wenchuan County and Mao County simultaneously. The actual survey procedure is described as follows: First, the staff in charge of all the schools and teachers in charge of all the selected classes were assembled, and the details of the survey and training on the main points of the research were given. Second, the questionnaires for the schools and teachers were distributed to the staff in charge of each school, and special notifications were given when handing out the forms. The questionnaires for the schools and teachers were filled in by the concerned persons, and were then gathered back in each school and handed over to our investigators. The investigators checked the submitted questionnaires and returned the forms that miss any relevant information or that were obviously flawed, requiring that such forms be redone; Third, the questionnaires for the students are distributed to the teachers in charge of each class, and special notifications were given when handing out the forms. Each teacher in charge of a class generally spent the time of one class to explain all the questions, and then guided the students to fill in the forms from the beginning to the end. The investigators gave technical instructions to aid the process, and finally checked the gathered questionnaires one by one.

Collection of high school and college entrance exam records for all the sample students were administered by the county education bureau of Wenchuan and Mao County.

4. Data

Following this sampling approach, we selected 90 classes in Wenchuan County and 37 in Mao County. We estimated the sample to include 4,291 students from Wenchuan County and 1,663 from Mao County, totaling 5,954 students. The students belonged to 12 primary schools, 2 middle schools, and 2 high schools in Wenchuan County and 3 middle schools and 1 high school in Mao County. After a week of field research, we finally gathered the samples comprising 5,482 students and 980 teachers from 20 schools in Wenchuan County and Mao County. The exact figures are given in Table 7.1.

Table 7.1: Number of Respondents in Our Study

County	School type	Students	Teachers	Present schools	Schools before the earthquake
Wenchuan	Primary School	1219	288	12	16
	Middle School	626	86	2	3
	High School	2159	253	2	3
Mao	Middle School	733	252	3	7
	High School	745	101	1	1
Total		5482	980	20	30

The actual number of students in the samples is less than the expected total of 5,954. There are mainly two reasons for this discrepancy: First, the number of students that the education bureau of the two counties gave us was different from the actual number of students in the classes we visited. The number reported by the education bureau was higher, so there was a statistical error. Second, some students were absent on the day we visited the classes, so we could not include them in the investigation. The number of these students is approximately 2% of the whole sample size, which is the factor that we could not control.

4.1. Natural Experiments

To identify the causal impacts of the earthquake on the psychosocial and cognitive outcomes of children, we have two sources of exogenous variations—or serendipitous "natural experiments"—which we investigate in this paper. First, the physical and human losses caused by the earthquake are treated as unforeseen exogenous shocks. In order to utilise this natural experiment, we conduct an additional survey of Mao County, a nearby county with a lower level of damage, to identify the causal impacts of the earthquake by comparing Mao and Wenchuan counties. Tables 7.2 and 7.3 compare the household and school damage, respectively, in the two counties. Table 7.2 shows that the intensities of home damage and negative job impacts are greater in Wenchuan County than in Mao County. Yet, surprisingly, the proportion of households whose income and consumption declined is slightly smaller in Wenchuan County than in Mao County. This probably reflects the fact that Wenchuan County received disproportionate amounts of external support after the earthquake. Table 7.3 shows the school and classroom damage in the two counties. Obviously, the intensity of damage is much larger in Wenchuan County than in Mao County. Also, Table 7.4 summarises the variables on damage and environmental changes that we use in this study.

Table 7.2: Household-Level Damage (In Percentage)

	Houses collapsed	HH member unemployed	Income declined	Food consumption declined
Wenchuan	26.77	25.34	75.03	45.04
Mao	16.14	10.06	82.63	47.55

Table 7.3: School and Classroom Damage(In Percentage)

	Serious damage of first floor	Serious damage of equipment	Serious human injury or loss at the school
Wenchuan	9.52	90.91	9.09
Mao	0	62.50	0

Table 7.4: Variables on Damage and Environmental Changes

Damage to households and individuals
Member(s) killed or injured
Member(s) became unemployed
Damage at school level
Serious human injury or loss at the school
Serious physical damage to the school
Environmental changes of education
Teacher and student environment change in temporary school
Teacher and student environment change in new school
Moved outside of county
Broad peer effects
(Outside Wenshuan) Teachers' interaction and communication with local school and community
(Outside Wenshuan) Donation from government and society
(Outside Wenshuan) Students' interaction and communication with local school and community
(Outside Wenshuan) Treatment of local government and volunteers

Another source of natural experiment is the peculiar decisions regarding school allocation in Wenchuan County after the earthquake. Of all the earthquake regions, only Wenchuan County decided to allocate most of the students outside the county after the earthquake. The decision was mainly made by the Wenchuan County education bureau, as it realised there was not enough safe space to build temporary schools and resettle the students within the county. The county education bureau asked the provincial education bureau to help with finding the destination schools that Wenchuan students could go to. The matching of Wenchuan schools and outside schools was not necessarily done in a systematic way. Personal connections, the willingness of enterprises, and administrative power all played a role in the process. For example, a private enterprise in Shanxi came to Wenchuan and expressed its willingness to move the middle school and high school at the epicenter (Yingxiu township) to Shanxi, and cover all the cost of the relocation.

In most cases, the students in one school moved together to one destination and almost all teachers moved with them. All the teachings were carried out by their own teachers during the relocation period. Local governments or enterprises at the destination provided the school buildings and financial support. In some cases, Wenchuan students might have shared the same school with the local students, but when possible, they usually had separate buildings. A small portion of Wenchuan students did not go with their schools but went to other schools their parents found for them. Very few dropped out of school temporarily.

This situation indicates that students and teachers in Wenchuan County were exposed to the outside schools exogenously. In other words, the classroom and school level peer effects were changed exogenously. This natural experiment will help identify how the peer effects affect the psychosocial and cognitive outcomes of students.

4.2. Psychosocial and Cognitive Outcomes

In order to capture the non-cognitive skills of children, we employ four different measures in this paper (see Table 7.5). First, we adopt the Center for Epidemiological Studies Depression Scale (CES-D), based on questions shown in Table 7.5 (A). This is one of the most popular measures to capture depression. We aggregate and rescale the responses so that the CES-D indicator is increasing in less depression. Second, we utilise the Strengths and Difficulties Questionnaire (SDQ) developed by Goodman (1997) to quantify the psychological attributes in conduct and peer relationship problems (Table 7.5 [B]). The third measure is the Rosenberg Self-Esteem Scale assessment, which measures perceptions of self-worth (Rosenberg, 1965). This is a 10-item scale, designed for adolescents and adults, and measures an individual's degree of approval or disapproval toward himself (Table 7.5 [C]). The final measure is the Family Environment Scale (FES), developed by Moos and Moos (1976), to measure the social-environmental characteristics of a family (Table 7.5 D). All these four measures are normalised and rescaled so that each measure is increasing in better psychosocial situations. The average measures in each county are shown in Table 7.6; in general, psychosocial situations seem to be better in Wenchuan County than in Mao County, intriguingly.

Table 7.5: Psychological Measures

(A) Depression

a. I don't want to eat. I have lost my appetite.	1. never____ 2. occasionally____ 3. sometimes____ 4. often______
b. I feel depressed.	1. never____ 2. occasionally____ 3. sometimes____ 4. often_________
c. I lack strength to do anything.	1. never____ 2. occasionally____ 3. sometimes____ 4. often______
d. I do not sleep well.	1. never____ 2. occasionally____ 3. sometimes____ 4. often_________
e. I feel happy.	1. never____ 2. occasionally____ 3. sometimes____ 4. often______
f. I feel lonely.	1. never____ 2. occasionally____ 3. sometimes____ 4. often_________
g. People are not friendly to me.	1. never____ 2. occasionally____ 3. sometimes____ 4. often______
h. I live a happy life.	1. never____ 2. occasionally____ 3. sometimes____ 4. often_________
i. I feel worried.	1. never____ 2. occasionally____ 3. sometimes____ 4. often______
j. I feel people hate me.	1. never____ 2. occasionally____ 3. sometimes____ 4. often_________
k. I feel people dislike me.	1. never____ 2. occasionally____ 3. sometimes____ 4. often______
l. everything about me is not progressing.	1. never____ 2. occasionally____ 3. sometimes____ 4. often_________

(B) SDQ

a. I am very cranky and usually get angry.	1. wrong_____2. somewhat right_____3. completely right_______
b. Usually I do what people tell me to do.	1. wrong_____2. somewhat right_____3. completely right____
c. I often fight.	1. wrong_____2. somewhat right_____3. completely right_______
d. People often say that I am lying.	1. wrong_____2. somewhat right_____3. completely right____
e. I have taken things not belonging to me.	1. wrong_____2. somewhat right_____3. completely right_______
f. I usually like to be alone.	1. wrong_____2. somewhat right_____3. completely right____
g. I have at least one friend.	1. wrong_____2. somewhat right_____3. completely right_______
h. My peers generally like me.	1. wrong_____2. somewhat right_____3. completely right____
i. Those younger than me fool me.	1. wrong_____2. somewhat right_____3. completely right_______
j. Compared with my peers, I get on better with those older than me.	1. wrong_____2. somewhat right_____3. completely right____

(C) Rosenberg Self-esteem

a. I am generally satisfied with myself.	1. very disagree__ 2. disagree___ 3. agree___ 4. very agree____
b. Sometimes I feel I am totally powerless.	1. very disagree__ 2. disagree___ 3. agree___ 4. very agree____
c. I feel I have many merits.	1. very disagree__ 2. disagree___ 3. agree___ 4. very agree____
d. I can do as well as others.	1. very disagree__ 2. disagree___ 3. agree___ 4. very agree____
e. I think I have nothing to be proud of.	1. very disagree__ 2. disagree___ 3. agree___ 4. very agree____
f. Sometimes I feel I am useless.	1. very disagree__ 2. disagree___ 3. agree___ 4. very agree____
g. I feel I am a valuable person, at least the same as the others.	1. very disagree__ 2. disagree___ 3. agree___ 4. very agree____
h. I hope I can earn myself more respect.	1. very disagree__ 2. disagree___ 3. agree___ 4. very agree____
i. Generally, I am inclined to consider myself a loser.	1. very disagree__ 2. disagree___ 3. agree___ 4. very agree____
j. I have a positive evaluation of myself.	1. very disagree__ 2. disagree___ 3. agree___ 4. very agree____

(D) Family conflict

a. My family members always give me their utmost help and support.	1.right_____ 2.wrong___
b. My family members often quarrel.	1.right_____ 2.wrong___
c. I feel bored with my family.	1.right_____ 2.wrong___
d. My family members seldom show their anger openly.	1.right_____ 2.wrong___
e. My family members are willing to put in much effort to do all things at home.	1.right_____ 2.wrong___
f. Some of my family members crush things when they get angry.	1.right_____ 2.wrong___
g. There is a harmonious atmosphere in my family.	1.right_____ 2.wrong___
h. My family members seldom get angry with one another.	1.right_____ 2.wrong___
i. Rarely is anybody willing to take up what must be dealt with at home.	1.right_____ 2.wrong___
j. My family members often criticise one another.	1.right_____ 2.wrong___
k. My family members always sincerely support one another.	1.right_____ 2.wrong___
l. My family members sometimes fight with one another.	1.right_____ 2.wrong___
m. My family lacks a teamwork atmosphere.	1.right_____ 2.wrong___
n. My family members try to reduce their differences, and keep good manners even when they have different opinions.	1.right_____ 2.wrong___
o. My family members get on well with one another.	1.right_____ 2.wrong___
p. My family members often want to excel others.	1.right_____ 2.wrong___
q. Every member in my family has been paid full attention to.	1.right_____ 2.wrong___
r. In my family, we feel that quarrelling with loud voices will not help solve problems.	1.right_____ 2.wrong___

Table 7.6: Psychological Measures by County and School Type

Wenchuan	CESD	SDQ	Self-esteem	FES
Primary school	0.382	-0.073	0.036	0.083
Middle school	0.094	-0.024	0.031	-0.030
High school	-0.115	0.122	0.041	0.020
Total	0.147	-0.012	0.035	0.018
Mao				
Middle school	-0.291	-0.116	-0.119	-0.087
High school	-0.373	0.060	-0.069	-0.101
Total	-0.331	-0.029	-0.094	-0.094

As to cognitive achievements, we use the Chinese and mathematics test scores for the end of academic years 2008 and 2009. Both the tests are given in July. Moreover, we use the study hours in July 2008 and July 2009 to capture the intensity of study. Table 7.7 shows that the test scores improved in Wenchuan County but deteriorated in Mao County.

Table 7.7: Changes in Official Test Scores and Study Hours

	Test scores–Chinese 2008	Test scores–Chinese 2009	Test scores–Math 2008	Test scores–Math 2009	Study hour 2008	Study hour 2009
Wenchuan						
Primary school	-0.005	-0.008	-0.004	-0.007	1.596	1.383
Middle school	-0.034	-0.023	-0.040	-0.025	1.991	1.954
High school	-0.037	-0.131	0.036	-0.064	2.121	2.188
Total	-0.024	-0.035	-0.017	-0.026	1.882	1.806
Mao						
Middle school	0.985	-0.021	0.786	-0.027	1.966	2.029
High school	0.017	0.011	0.000	0.016	2.529	2.440
Total	0.028	-0.005	0.008	-0.004	2.239	2.229

5. Econometric Model and Estimation Results

In order to examine the relation between the disaster variables shown in Table 7.4 and the outcome variables such as the psychological measures in Table 7.5 and test scores, we set up an econometric model of each outcome variable, Y. Note that each damage variable is treated separately as a dichotomous variable D, which takes the value of 1 if damage arises, and zero otherwise. In other words, we postulate a model of treatment of disaster damage using the natural experimental nature of disasters. The level of an outcome variable with damage is denoted by Y^1, and without damage is denoted by Y^0. The average impact of damage caused by a disaster is shown as the following average treatment effects of the treated (*ATT*):

$$E(Y^1 - Y^0 | D=1). \tag{1}$$

In equation (1), the fundamental issue is the way to grasp the counterfactual outcome, $E(Y^0|D=1)$, which cannot be observed directly. Rewriting equation (1), we obtain

$$\begin{aligned} (2) \quad & E(Y^1|D = 1) - E(Y^0|D = 0) \\ & = [E(Y^1 = 1|D = 1) - E(Y^0|D = 1)] + [E(Y^0|D = 1) - E(Y^0|D = 0)] \\ & = E(Y^1 - Y^0|D = 1) + [E(Y^0|D = 1) - E(Y^0|D = 0)]. \end{aligned}$$

Equation (2) shows that the observable average difference between the treatment and control groups, i.e., $E(Y^1|D = 1) - E(Y^0|D = 0)$, deviates from *ATT*, $E(Y^1 - Y^0|D = 1)$, by the amount $E(Y^0|D = 1) - E(Y^0|D = 0)$. This discrepancy is called a selection bias, which basically shows the discrepancy between the average outcome of counterfactual situation $E(Y^0|D = 1)$ and the average observable outcome of the control group $E(Y^0|D = 0)$. Since disasters are unforeseen contingencies and cannot be manipulated by humans, they provide researchers with natural experiments in a sense similar to DiNardo (2008), in which people are exogenously assigned into treatment and control groups. We assume that such a natural experiment gives us a serendipitous situation where the selection bias [$E(Y^0|D = 1) - E(Y^0|D = 0)$] converges to zero. Indeed, studies such as Kahn (2005) show that there is no systematic relationship between the observed income level and degree of disaster damage. Yet, it may be also true that post-disaster outcomes are also affected by pre-earthquake characteristics of each household or individual, and the condition [$E(Y^0|D = 1) - E(Y^0|D = 0)$] = 0 may not be satisfied in general. To handle this potential problem, we assume that given the same set of observables X, the selection bias becomes zero; i.e.,

$$E(Y^0|D = 1, X) - E(Y^0|D = 0, X) = 0. \tag{3}$$

This assumption is called ignorability, or selection on observables. To check the plausibility of this assumption, we perform a few balancing tests between the treatment and control groups following Bruhn and McKenzie (2009) and Imai *et al*., (2008). Using the student characteristics such as age, height, and sex, as well as pre-disaster household asset ownership as the elements of X, we confirm that the balancing tests are passed.

Furthermore, assuming a linear conditional expectation function and the ignorability of equation (3), we rewrite equation (2), conditional on observables X, as follows:

$$Y = \alpha + \delta D + X\gamma + u. \tag{4}$$

Also, for test scores and study hours, we have individual panel data before and after the disaster, and estimate the difference-in-difference model of equation (4):

$$\Delta Y = \alpha^d + \delta^d D + X\gamma^d + u^d, \tag{5}$$

where Δ is a first-difference operator. We quantify *ATT* by estimating the parameters δ in equation (4) and δ^d in equation (5). Admittedly, several potential problems are left behind in estimating equations (4) and (5), so we take the analysis in this paper as our primary approach.

5.1. Unconditional *ATT*

We first estimate *ATT* based on equation (4) without the control variable *X*. In this case, *ATT* is quantified simply as a difference of the average value of the outcome variable between the treatment group (D = 1) and control group (D = 0). As a treatment variable, *D*, we use four indicator variables interchangeable for household member damage (killed or insured), unemployment due to earthquake, school-level human loss, and relocation of classroom/school outside the county.

Table 7.8 shows the *ATT* for each of the treatment variables using psychology and the family environment variables as outcomes, i.e., the Center for Epidemiologic Studies Depression scale (CES-D), the Strengths and Difficulties Questionnaire (SDQ) measure, the Rosenberg Self-Esteem Scale (RSES), and the Family Environment Scale (ES). We have two main findings from Table 7.8. First, household level damage uniformly worsens the psychosocial measures. In particular, the negative impacts on depression and family environments seem to be significant. Second, while school-level damage and changes seem to generate opposite effects, the effects of school-level human damage are not statistically significant. Classroom relocation helps to improve depression problems as well as enhance self-esteem significantly.

Table 7.8: Unconditional ATT of Exogenous Shocks on Non-Cognitive Outcomes

	N_CESD	N_SDQ	N_Rosenberg	N_FES
	CES-D	SDQ	RSES	FES
Treatment variable (household level)				
Household member(s) killed or injured	-0.103**	-0.053	-0.024	-0.085**
Household member(s) became unemployed	-0.175**	-0.159**	-0.111**	-0.112**
Treatment variable (school level)				
Serious human losses at school	0.006	-0.006	0. 075	-0.039
Relocated outside the county	0.267**	0.061	0. 145**	0. 082**

Note: ** and * show statistical significance at the 1% and 5% levels, respectively.

In Table 7.9, the earthquake impacts on cognitive outcomes captured by the Chinese and mathematics test scores as well as self-reported study hours are shown from the estimations of the difference-in-difference model of equation (5) without control variables, *X*. According to the estimation results, while household-level damage generates statistically insignificant impacts on test scores, school-level s improve test scores.

Table 7.9: Unconditional ATT of Exogenous Shocks on Cognitive Outcomes

	Change in Chinese test score	Change in Chinese (entrance) test score	Change in math test score	Change in math (entrance) test score	Change in study hours
Treatment variable (household level)					
Household member(s) killed or injured	-0.027	0.050	0. 002	0.027	0. 021
Household member(s) became unemployed	0. 012	0.059	-0.033	0.018	-0. 004
Treatment variable (school level)					
Serious human losses at school	-0.086	0.174	-0.145	-0.022	0 .159*
Relocated outside the county	0. 027	0.007	-0.016	0.112	-0.111**

Note: ** and * show statistical significance at the 1% and 5% levels, respectively.

According to Tables 7.8 and 7.9, we see heterogeneous effects of household- or individual-level earthquake damage on outcomes. Yet, before drawing conclusions based on these unconditional *ATT*s, we examine *ATT*s conditional on observables.

5.2. Conditional *ATT*

We estimate equations (4) and (5) conditional on observables such as student grade year, age, sex, and height, household pre-earthquake asset ownership, and parent education levels. To capture the non-essential heterogeneous treatment effects, we include multiple disaster variables in each specification shown in Table 7.10. Four main findings emerge from our estimation. First, household-level damage due to human loss and/or unemployment worsens all psychosocial measures and family environment measures uniformly. In particular, the depression problems that arise and the impacts generated by unemployment seem to be serious. Since after a disaster, emergency employment can be generated effectively by the government, this finding indicates the importance of an effective public policy after a disaster.

Table 7.10: Conditional ATT of Exogenous Shocks on Non-Cognitive and Cognitive Outcomes

	Non-Cognitive Human Capital				Cognitive Human Capital				
	CES-D	SDQ	RSES	FES	Change in Chinese test scores	Change in Chinese (entrance) test score	Change in math test scores	Change in math (entrance) test score	Change in study hours
Treatment variable (household level)									
Household member(s) killed or injured	-0.152*	-0.006	-0.056	-0.148**	-0.064	0.0003	0.000	0.009	0.022
Household member(s) became unemployed	-0.292**	-0.216**	-0.212**	-0.189**	-0.075	0.088*	-0.048	0.04	-0.045
Treatment variable (school level)									
Serious human losses at school	0.149**	0.003	-0.002	0.014	0.095*	0.136	0.173**	-0.012	0.086
Serious physical damage to school	0.141**	-0.003	0.043	-0.066**	0.169**	-0.106	0.101**	-0.055	0.023
Relocated outside the county	0.229**	0.083	0.24**	0.154**	0.075*	-0.07	-0.069	0.077	0.1
Study environment improvements	0.003	-0.003	0.015*	-0.007	0.029**	-0.002	-0.003	-0.04	0.025*
N	2732	2741	2736	2744	2693	3375	2693	3375	2715
R-squared	0.06	0.04	0.05	0.03	0.02	0.09	0.02	0.05	0.02

Note: We control for student grade level dummies, age, sex dummy, and height, household-level pre-disaster asset ownership, and parents' education level variables.

** and * show statistical significance at the 1% and 5% levels, respectively.

Second, intriguingly, the school/classroom-level damage and changes, captured by school building damage and classroom relocation outside the county, seem to improve psychosocial outcomes as well as cognitive outcomes, captured by test scores. In particular, classroom relocations mitigate depression, enhance self-esteem, and improve family environment.

Third, as to their influence on cognitive outcomes, household-level damage has insignificant impact. In contrast, school/classroom-level damage and changes improve test scores uniformly. We also observe marginal positive impacts on study hours. These positive effects of the Sichuan earthquake on cognitive outcomes are consistent with the findings of Park and Wang (2009), who collected and analysed a different dataset from the Sichuan earthquake victims. In particular, the positive coefficients of relocation outside the county and of improvements in study environment on Chinese test scores may reflect positive peer effects through the earthquake-affected students' unexpected exposure to students and facilities in better schools. While positive effects may arise from the solidarity of the relocated students who live together, in fact, on additional analysis, which is not shown in this paper, we find that among the relocated classrooms, the teachers' interaction and communication with the destination school and community are positively related with both the Chinese and mathematics test scores of the relocated students, confirming positive peer effects.

Fourth, the impact of school damage and relocation on cognitive outcomes faded out after all the students had come back to their newly constructed schools, as shown by the changes of their Chinese and math entrance exams. Reconstruction of new schools with high quality may mitigate the negative impact of the earthquake in the short term.

Yet, improvements in psychosocial measures may be a reflection of the students' mental problems such as survivor guilt among the control schools. If this interpretation is true, a disaster may generate negative psychosocial impacts indirectly through strong negative externalities. This implies that post-disaster mental care services should be provided not only to children in the directly affected schools, but also to students in the unaffected schools.

6. Concluding Remarks

In this paper, we employ original micro data collected from the students and schools affected by the Great Sichuan Earthquake to uncover the impacts of the earthquake on students' cognitive and non-cognitive outcomes. There are two main findings. First, the household-level shocks due to the earthquake worsen the child psychosocial as well as family environmental outcomes uniformly. Second, classroom relocations due to earthquake mitigate depression, enhance self-esteem, improve family environment, and improve Chinese test scores. These effects may reflect positive peer effects through the earthquake-affected students' unexpected exposure to students and facilities in better schools.

These findings indicate that there exist clear asymmetries in the impact of natural disasters on child cognitive and non-cognitive outcomes. The impact may differ greatly owing to the type and level of damage caused by a disaster. This suggests that children's post-disaster mental care should be carefully designed and customised in such a way that their human capital development processes are amended and facilitated effectively. In particular, the students who encounter serious losses and damage to their households should be provided with intensive psychological care. Also, we find that if carefully organised, the temporary relocation of affected students may mitigate the negative consequences of natural disasters, possibly through positive peer effects from their new school environment. Reconstruction of high quality new schools also helps mitigate the negative impact of school damage.

As opposed to the emphasis on cognitive skills or personality traits in human capital accumulation in the literature, James Heckman and his associates tried to address the importance of non-cognitive skills as determinants of economic and social outcomes (Heckman and Rubinstein, 2001; Heckman *et al*., 2006). While children's cognitive abilities appear to be fairly well determined by an early age, their non-cognitive skills such as motivation and self-discipline are more malleable at later ages than their cognitive skills. Mentoring and motivational programs oriented toward disadvantaged teenagers seem to be effective in the United States. In case such a mechanism is applied also to China (Glewwe *et al*., 2011), the government might play an important role in amending the non-cognitive skills of children affected by natural disasters directly or indirectly. Concrete forms of public intervention include a variety of customised counseling services to treat post-traumatic stress disorders (PTSD) like survivor guilt, mentoring programs by senior people in the community, and temporal relocation of classrooms to outside of the disaster areas. These policies would render human capital investments in a broader sense effective.

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CHAPTER 8
Do Short-term Indoor Park Programs Improve Preschool Childer's Psychological Health in Fukushima?*

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Due to serious concerns about radiation exposure after the nuclear power plant accident, many parents in Fukushima prohibited their children from playing outdoors. The Japanese Red Cross organized short-term and large-scale indoor park programmes for preschool children across Fukushima to mitigate concerns about high stress levels among the children. Our research aimed to quantify the impact of these short-term indoor park programmes on the children's psychological health. We employed the Strengths and Difficulties Questionnaire to try and capture the children's psychological health conditions. Although no causal statement may be made regarding the programme's effectiveness due to lack of randomization, participation in the programme is not negatively correlated with the average stress level; indeed, we observed some signs of positive correlation with the overall stress level and negative correlation with pro-social behaviours. This correlation was largely found among the children whose parents always prohibit them from playing outdoors and who regularly use the indoor playground facilities. This may be due to an actual impact, reporting bias (those who want the program to continue may overstate the stress level in order to appeal the need of the program), or reverse causality. We also found that stress is correlated with the experience of evacuation and parents' prohibition of outdoor play, but not in the cases of those children who participated in the regular indoor programmes.

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1. Introduction

The March 11th 2011 disaster in Tohoku, Japan, was a natural disaster comprising an earthquake and tsunami, which also resulted in a high-level technological disaster involving massive radioactive contamination from the Fukushima Dai-ichi nuclear power plant. One of the most detrimental and long-term consequences of the Fukushima nuclear power plant accident has been the deprivation of an appropriate environment for children to grow up healthily. A number of studies revealed that early childhood development has a significant impact on well-being in adulthood (Carniero and Heckman, 2003; Currie and Almond, 2011; Duncan and Magnuson, 2013), and in Chernobyl the largest public health consequence of the 1986 nuclear disaster was said to be concerning mental health (Bromet, 2012). A recent longtitudinal survey in Fukushima documented that stress levels are significantly higher there than in the other regions of Japan (Fukushima prefecture, 2011; Tsutsui *et al*., 2011). What can be done to mitigate such concerns?

This research aims to estimate the extent to which the short-term indoor park programmes in Fukushima can improve the psychological health of the children whose stress levels are high as a consequence of the nuclear power plant accident. While previous studies on early childhood development have investigated the long-term consequences of nutritional and cognitive deterioration in early life as a consequence of a natural or manmade disaster (Almond *et al*., 2010; Almond *et al*., 2009; Banerjee *et al*., 2010; Yamano *et al*., 2005; Paxson and Schady, 2005), no study so far has examined the effectiveness of a short-run policy intervention. Originally, the programme had intended to incorporate a lottery procedure as it had expected a large volume of applications from kindergartens. This could have helped significantly in the identification of a causal impact. But due to the unexpectedly low number of applications, the programme was able to accept all applications and no lottery took place, making a clear identification of causal impact impossible.

We found that participation in the programme was not significantly correlated with the overall stress level. Nevertheless, three significant tendencies could be observed: first, the stress level was significantly lower than in the surveys conducted in the previous years. Second, the parents' risk aversion behaviours decreased compared with the previous years. Third, the stress level of children was positively and modestly correlated with the experience of evacuation as well as parents' prohibition of outdoor play. Overall, the study confirmed that the major trends such as the natural decline of stress over time and the experience of evacuation may be a much more important factor than short-term interventions.

Furthermore, participation in the indoor park programmes is occasionally positively correlated with the stress level, which is inconsistent with our qualitative observations. These correlations were concentrated among those who do not regularly play outdoors, and instead use indoor playground facilities. We cannot know whether this was because of actual impact, reverse causality, or reporting bias. Given that the individual participation variables (which are more endogenously decided than the overall participation variable) were not significant, it may be that the parents had reporting bias in the opposite direction of that originally expected—parents who have a need for indoor facilities and realised the benefits of the Red Cross programme may have overstated the children's stress level so as to induce the Red Cross to continue the programme.

The remainder of this paper is organised as follows. In Section 2, we provide the research background including a brief literature survey on early childhood development, the overall psychological and children's environment in Fukushima after the nuclear accident, and a detailed description of the indoor park programme organised by the Japanese Red Cross. Section 3 describes the nature and summary statistics of data, which we collected exclusively for the present study. The results of regression analysis are presented in Section 4, which is followed by concluding remarks in the final section.

2. Background

2.1. Early childhood environment and psychological well-being

Depression has serious consequences on economic productivity, and most adult psychiatric disorders have their roots in early life. Economists have recently begun to explore the issues of depressive disorder and poverty (Haushofer and Shapiro 2013), and point to the possibility of poverty trap based on poor decision-making capacity (Shah *et al*., 2012). About 22 percent of people in Japan experience depression in the course of their lives (Bromet *et al*., 2011), and this leads to poor decision-making and lower productivity. The prevalence of depressive disorders among the population increased by 37 percent between 1990 and 2010, and is now a leading contributor to the global burden of disease (Murray *et al*., 2012). In 2004, the health issue leading to the highest Years Lost due to Disability for both men and women was unipolar depression. Given the magnitude of this problem, it is critical to identify effective policies to prevent it.

Multiple psychiatric research has found that psychiatric disorders can be traced back to symptoms in adolescence. (Kim-Cohen *et al*., 2003; Pine *et al*., 1998) Furthermore, a number of economists have pointed out the lasting benefits of early childhood interventions in terms of nutrition and educational programmes (Carniero and Heckman, 2003; Currie and Almond, 2011; Duncan and Magnuson, 2013) In 2006, the Chernobyl Forum concluded that mental health was the largest public health concern after the disaster. As the situation in Fukushima is similar in terms of the contamination issue, it is critical to investigate what policies could be effective to reduce stress levels, and the possible psychiatric problems in adulthood that may arise as a consequence.

2.2. Psychological health and children’s environment in Fukushima after the nuclear accident

The Fukushima Dai-ichi nuclear power plant radiation accident was classified as level 7 by the International Atomic Energy Agency—the highest level on International Nuclear Event Scale—and had been the most serious nuclear disaster since the 1986 Chernobyl disaster. It has led to stress levels of parents and children substantially higher than in other parts of Japan. This is due not only to multiple socioeconomic changes, such as migration and stagnation of agriculture, but also to conflicting information regarding the safety of nuclear exposure. Because of their concerns, mothers resorted to risk aversion behaviour, such as avoiding to purchase local vegetables or giving up checking radiation meters.

Nevertheless, playing outdoors has steadily resumed at family homes and kindergartens from 2012 until the present, for the following two reasons: First, while often incomplete, decontamination has been taking place through multiple steps. Second, according to the kindergarten teachers, adults have realized the harm of prohibiting children from playing outside, which leads to a weakening of children's physical capacities. They note, for instance, that children sometimes fall down when first running outside even though they had been running well indoors. So many parents feel they cannot just stop children from going outside. But promoting outdoor play in kindergartens may take a long time as it requires a consensus among mothers. Some children currently play outside as their parents allow it, while others do not. Consequently, as of January 2014, many kindergartens have been limiting the duration of outdoor play, usually to up to 30 minutes per day

2.3. Details of the indoor park programme

Various non-profit organisations (NPOs) and municipalities have been making efforts to provide alternative indoor parks in Fukushima prefecture. The Japanese Red Cross has been organising large-scale and short-term indoor playgrounds throughout Fukushima over the past years.[2] The programme aims to provide outdoor playing facilities for preschool[3] children affected by the nuclear power plant accident, to give them space to reduce their stress levels and improve their physical capacity.

The indoor park programme in Koriyama lasted for 11 days, and brought together a total of around 1,500 children. The number of applications had been significantly lower than originally expected given Koriyama's large population, probably due to the fact that the city already had a permanent large-scale indoor park.[4]

The indoor park provided by the Red Cross consisted of morning and

[2] This was one of many programmes the Japanese Red Cross organised that made use of overseas aid. The overall cost amounted to over one million US dollars, which was covered by overseas donations. A large portion of the cost went into hiring local staff to monitor children's play, as it was critical to avoid injuries in the indoor environment.

[3] In Japan, preschools consist of kindergartens and nursing schools. Kindergartens are for three years whereas nursing schools are for four years, and targeted at households whose mothers also work.

[4] Although the programme was designed to be different from the permanent one, it still resembled it to a large extent.

afternoon sessions—children from selected preschools participated in the morning sessions, while any individuals from the community could participate freely in the afternoon sessions. The programme included air-based equipment and physical education-oriented programmes. Moreover, a show involving the popular character Anpan-man was held, at the end of which children were given small toys.

3. Data

We used a so-called Strength and Difficulties Questionnaire (SDQ) to assess the children's psychological health (Goodman, 1997; Matsuishi *et al*., 2008). We selected SDQ measures because it is one of the most widely used measures of children's psychological attributes and thus its use allows us to preserve comparability with other studies conducted in Japan and Fukushima prefecture. The largest limitation is that SDQs are designed mainly for tracking long-term circumstances and are less well suited for capturing short-term trends. To consider the change over time, we also asked questions regarding how the situation changed over the past month.

To achieve a high overall response rate, we surveyed both parents and preschool teachers regarding the same questions: SDQ has separate sections for parents and teachers. The correlation between the two measurements was significant. At the same time, Analysis of Variance (ANOVA) Interclass correlation coefficient (ICC)[5] was 0.35, which is too low to claim that two measurements are on the same subject. Taken together, these measurements indicate that teachers and guardians are looking at correlated yet different aspects of children's behaviour, which may be the case because children behave differently between homes and preschools. The behavioural questions related to the risk of radiation exposure were taken from the questionnaires of the Children's Stress Assessment Survey developed by Tsutsui *et al*. of Fukushima University. Overall, the response rates were 73.5 percent for preschools, 69.2 percent for teachers, and 79.7 percent for parents (25 preschools out of 34 places; among teachers, 355 out of 513 children; among parents, 409 out of 513 children). These response rates were approximately the same as in the other surveys we conducted. However, it can be questioned

[5] This reliability test was intended in the pre-analysis plan.

how representative the survey is as it targeted only at the preschools that applied to the indoor park programme. If there were to be any directional bias, we expect the reported stress level to be higher among the participating preschools because participation indicates some concern about psychological and physical health. We complemented the quantitative data with some qualitative questionnaires filled out by preschool administrators.

This study was endorsed by the Koriyama City children's support division, the private kindergarten association, the approved nursing school chairman's committee, and the private nursing school association, and the expedited review from the Institutional Review Board of the University of Tokyo.

3.1. Summary Statistics

An overall comparison with the previous survey conducted in 2011 shows that the stress level has decreased significantly over the past two years. Whereas previously 24.9 percent of children needed assistance (above 16 points in the SDQ), this fell to 10.1 percent in our latest survey. The score is still marginally higher than the Japanese average (1 point), but the difference is smaller than the minimum important change (3 point)[6].

We found that 35 percent of the children have experience of evacuation. The amount of time preschools allow children to play outside varies considerably between preschools. The table below shows that the risk attitude remains high even three years after the accident:

Behavioural response to the accident

Percent (n=409)	Regularl	Sometime	Not
Open window to exchange air	43.3	44.5	8.1
Let children play outside	31.6	54.3	11.7
Check radiation meter	39.4	39.6	19.8
Purchase vegetables made in	4.4	73.6	21.5

[6] In epidemiology, it is common to consider about a half of the baseline standard deviation to be the minimum important change. In this survey, the baseline standard deviation was 5.1, so the minimum important change is about 2.55.

This highlights the steady recovery of outdoor play as compared to the Children's Stress Assessment Survey, although the prohibition still remains for some.[7] At the same time, the most anxious parents will perhaps continue to prohibit their children from playing outside.

4. Empirical Analysis

The analysis below was conducted in accordance with the pre-analysis plan. We included some additional analyses of interaction terms to enrich our analysis.

The outcome variables were the scores of SDQs in each of four sub-categories (emotional symptoms, conduct problems, hyperactivity/inattention, peer problems) and pro-social behaviours. Following the SDQ specification, a lower value is desirable for the first four symptoms, and a higher value is desirable for the last symptom. In addition, we also asked how these symptoms have changed over the month prior to the survey. The main concern for using this outcome variable is that recalling is often imperfect: the parents' and teachers' responses are uncorrelated, suggesting lack of consistency.[8] Nevertheless, it may shed some light on the trend, which the current situation variable cannot do, as there were no baseline surveys. The control variables include age, gender, number of siblings, wealth proxied by the preschool's location's land price[9], above-mentioned risk aversion behaviours, type of houses, experience of evacuation, a dummy indicating whether a child is in preschool, the size of the school (number of boys and girls in each year as well as its maximum capacity), the length of time it took to decontaminate the school playground[10], and the frequency of outdoor play

[7] Note that the target age of the survey is different: the Children's Stress Assessment Survey also includes primary school children.
[8] The change variable between teachers and parents indicates a significant degree of inconsistency compared with other outcome variables.
[9] This is arguably an imperfect measure. For instance, preschools near large stations may be used by low-income households of smaller size, but may have a high land price.
[10] The lack of decontamination can also arise from the low level of radiation to begin with. Thus, it is not necessarily clear whether it is better to have a longer or shorter duration.

at preschools[11]. We tried multiple levels of control variable inclusion, but results seem largely unchanged.

4.1. Overall trend

Table 8.1 presents some significant correlation between psychological health level and individual characteristics. Even though the differences are small in magnitude, we still found the following three trends that are statistically significant:

1. Children who have experienced evacuation tend to have higher stress levels (this is consistent with the results of Iwasaki and Sawada (2014), who found evidence of reference-dependence regarding the stress level among the evacuees from Futaba town in Fukushima prefecture), although the significance drops when all control variables are included;

2. Children living in their own family house or in a public servant's dormitory[12]" statistically have significantly lower stress levels than children who live in their relatives' homes;

3. Children whose parents do not permit outdoor play also have higher stress levels. 4.2 Balance check.

[11] Play per week in the preschool may be due to seasonal variation

[12] But note that the sample size is only seven for the public servant's dormitory. So, while it could be reflecting the stability of a public servant's job, it could be driven by small sample bias.

Table 8.1: Overall Trend of Psychological Health

Outcome:	Total SDQ Score											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Evacuation	1.269**	1.464***	0.770	0.750								
	(0.510)	(0.542)	(0.631)	(0.816)								
Public housing					-1.105	-0.833	-0.377	0.350				
					(1.445)	(1.195)	(1.226)	(2.137)				
Privately-owned house					-1.551	-1.858**	-0.195	0.746				
					(0.979)	(0.941)	(1.041)	(1.986)				
Close relative's house					-0.970	-0.735	0.346	1.169				
					(1.030)	(1.040)	(1.136)	(2.123)				
Public servant's dormitory					-5.664***	-5.133***	-5.115***	-4.160**				
					(1.048)	(1.036)	(1.276)	(1.713)				
Charter housing					-0.771	-0.948	0.632	1.530				
					(1.371)	(1.093)	(1.210)	(1.679)				
Company's dormitory					-1.812	-1.886	0.903	2.028				
					(1.874)	(1.968)	(2.417)	(2.616)				
Sometimes let children play outdoor									0.717	0.711	0.195	0.523
									(1.013)	(0.537)	(0.671)	(0.879)
Never let children play outdoor									3.451***	2.989***	2.672**	3.057***
									(1.000)	(0.919)	(1.114)	(1.019)
Constant	8.946***	8.876***	6.690*	8.444***	10.614***	10.705***	6.690*	8.444***	8.577***	8.636***	6.690*	8.444***
	(0.183)	(0.296)	(3.437)	(2.621)	(0.899)	(0.865)	(3.437)	(2.621)	(0.661)	(0.421)	(3.437)	(2.621)
Specification	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Controls	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Observations	402	402	322	322	393	393	322	322	399	399	322	322
R-squared	0.098	0.019	0.186	0.216	0.103	0.027	0.186	0.216	0.118	0.031	0.186	0.216

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. FE also has clustered standard errors at preschool levels.
For column (3) and (4), the omitted variable in the housing regression is the "far relative's house" (sibling's family's house). For column (5) and (6), the omitted variable in the outdoor regression is "always let children play outdoor." The control variables include personal characteristics for FE, and personal and preschools'

Table 8.2 presents the balance tests of the equality of basic individual characteristics between the treated and the control groups. Participation in the parents survey can be defined in six ways: participation (whether the child participated according to the guardian’s response either through the preschool programme or individually through afternoon sessions), individual participation (whether the child participated individually through afternoon sessions), number of participations, number of individual participations, preschool participation (whether the child participated through the preschool), and preschool participation intent-to-treat (ITT) (the number of times the child should have participated based solely on the preschool’s decision). There are two variables for the teacher’s survey: participation (whether the child has participated according to the teachers, complemented by the information from the preschool ITT variable) and the number of participants. Although we do not have the baseline measurement, this can shed some light on the reliability of these participation variables. We ran the following regression, and Table 8.2 reports α1. Here, i refers to each child and j refers to preschools.

$$x_{ij} = \alpha_0 + \alpha_1 Participation_{ij} + f_j + \varepsilon_{ij}$$

Table 8.2: Balancing Test with Parents Survey

	Outcome:	Gender		Grade		Siblings	
		(1)	(2)	(3)	(4)	(5)	(6)
Parents:	Participation	-0.068	-0.085	-0.143	-0.167	-0.265**	-0.077
		(0.072)	(0.086)	(0.096)	(0.133)	(0.131)	(0.150)
	Individual participation	-0.105*	-0.126***	-0.154**	-0.164*	-0.089	-0.105
		(0.057)	(0.037)	(0.071)	(0.081)	(0.086)	(0.071)
	Participation numbers	-0.079***	-0.092***	-0.119***	-0.091*	-0.077*	-0.028
		(0.027)	(0.021)	(0.045)	(0.048)	(0.041)	(0.037)
	Indiv part numbers	-0.090***	-0.089***	-0.126**	-0.121**	-0.048	-0.055
		(0.032)	(0.017)	(0.050)	(0.051)	(0.049)	(0.049)
	Preschool participation	-0.081	-0.150	-0.071	-0.042	-0.270**	-0.050
		(0.067)	(0.110)	(0.087)	(0.155)	(0.117)	(0.194)
	Preschool part ITT	-0.050	0.067***	-0.134	-1.000***	-0.323***	0.367***
		(0.078)	(0.000)	(0.094)	(0.000)	(0.124)	(0.000)
Teachers:	Participation	-0.012	0.131	-0.077	-0.559**		
		(0.080)	(0.163)	(0.085)	(0.214)		
	Participation numbers	-0.076	-0.128	-0.215***	-0.345***		
		(0.057)	(0.096)	(0.074)	(0.089)		
	Specification	OLS	FE	OLS	FE	OLS	FE

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. FE also has clustered standard errors at preschool levels.
The sample size ranges between 369 and 405 for each specification test. No control variables are included.

Both for parents' and teachers' surveys, we observe that the "participation" variables are the most balanced, both with respect to ordinary least squares (OLS) and preschool-fixed effect (FE). However, in general, female children with lower grades and fewer siblings are most likely to have participated many times. Participation numbers are largely driven by individual decisions, and therefore are more highly correlated with their characteristics than with the decision by the preschools. For pre-school ITT, we observe that the coefficient on the FE regression of grade is -1. This is a mechanical result because the variation within the ITT variation was limited to only one preschool, where three upper class (5-6 year-old) children did not participate. Therefore, ITT-FE regressions should not be taken too seriously as they would be driven by only three observations.

4.3. Total participations

Table 8.3 and 8.4 present the following regression on the participation variable, both for parents' and teachers' surveys.

$$y_{ij} = \beta_0 + \beta_1 Participation_{ij} + X_{ij}\beta_2 + f_j + \epsilon_{ij}$$

Table 8.3: Overall Regressions with Parents' Survey

	Total difficulties	Emotional symptoms	Conduct problems	Hyperactivit y /inattention	Peer problems	Prosocial behaviors	Change in total score	Change in prosocial behaviors
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS:								
Without controls								
Participation	0.524	-0.123	0.370	0.227	0.049	0.043	0.012	-0.007
	(0.711)	(0.288)	(0.239)	(0.300)	(0.189)	(0.273)	(0.033)	(0.032)
Number of participation	0.239	0.113	0.122	-0.079	0.082	-0.017	-0.000	0.003
	(0.323)	(0.135)	(0.102)	(0.127)	(0.088)	(0.124)	(0.015)	(0.015)
With controls								
Participation	0.434	-0.256	0.577*	0.078	0.034	0.179	0.061	-0.037
	(0.985)	(0.388)	(0.333)	(0.415)	(0.236)	(0.366)	(0.043)	(0.040)
Number of participation	0.497	0.310*	0.106	-0.063	0.145	-0.141	0.012	-0.010
	(0.428)	(0.160)	(0.158)	(0.168)	(0.110)	(0.170)	(0.015)	(0.020)
Preschool-FE:								
Without controls								
Participation	0.275	-0.331	0.513	0.159	-0.067	0.355	0.012	-0.009
	(0.980)	(0.361)	(0.325)	(0.364)	(0.192)	(0.453)	(0.031)	(0.030)
Number of participation	0.232	0.163	0.134	-0.128	0.063	0.060	-0.001	0.003
	(0.458)	(0.197)	(0.134)	(0.182)	(0.062)	(0.127)	(0.016)	(0.015)
With controls								
Participation	0.092	-0.350	0.525	-0.044	-0.039	0.528	0.049	-0.030
	(0.920)	(0.399)	(0.381)	(0.299)	(0.149)	(0.333)	(0.041)	(0.047)
Number of participation	0.336	0.271*	0.071	-0.124	0.119	-0.070	0.009	-0.012
	(0.460)	(0.139)	(0.183)	(0.206)	(0.074)	(0.138)	(0.010)	(0.025)

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. FE also has clustered standard errors at preschool levels.

Table 8.4: Overall Regressions with Teachers' Survey

	Total difficulties	Emotional symptoms	Conduct problems	Hyperactivity /inattention	Peer problems	Prosocial behaviors	Change in total score	Change in prosocial behaviors
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS:								
Without controls								
Participation	0.364	0.129	0.082	0.097	0.069	-0.592	0.274***	-0.217***
	(0.798)	(0.192)	(0.284)	(0.412)	(0.218)	(0.368)	(0.057)	(0.055)
Number of participations	-0.247	-0.044	0.056	-0.093	-0.109	0.233	0.202***	-0.128***
	(0.618)	(0.148)	(0.211)	(0.328)	(0.193)	(0.290)	(0.036)	(0.041)
With controls								
Participation	-4.983*	-0.354	-1.479*	-2.293	-0.674	3.105**	-0.062	-0.066
	(2.824)	(0.613)	(0.758)	(1.474)	(0.886)	(1.251)	(0.077)	(0.098)
Number of participations	-1.443	-0.363	0.076	-0.462	-0.701*	1.660***	0.086**	-0.094*
	(1.157)	(0.287)	(0.347)	(0.636)	(0.360)	(0.546)	(0.041)	(0.048)
Preschool-FE:								
Without controls								
Participation	-1.651	0.114	0.139	-0.943	-0.850*	1.553	-0.045	-0.051
	(2.038)	(0.369)	(0.629)	(1.248)	(0.425)	(1.224)	(0.063)	(0.036)
Number of participations	0.216	-0.093	0.435***	0.523	-0.704**	0.531	0.222***	-0.145***
	(0.790)	(0.098)	(0.065)	(0.396)	(0.332)	(0.565)	(0.072)	(0.036)
With controls								
Participation	-3.372	-0.248	-0.538	-1.210	-1.107**	2.978***	-0.089	-0.039
	(2.373)	(0.362)	(0.778)	(1.475)	(0.528)	(0.284)	(0.100)	(0.062)
Number of participations	-1.027	-0.347	0.201	0.137	-1.064***	1.218***	0.194**	-0.133***
	(1.300)	(0.251)	(0.256)	(0.677)	(0.259)	(0.137)	(0.077)	(0.043)

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. FE also has clustered standard errors at preschool levels.

Although no causal inference can be made from these regressions, the associations are mostly insignificant. For the ones that are significant, they mostly indicate that the programme is positively correlated with the psychological stress of the children. In particular, emotional symptoms and conduct problems are marginally higher among those who participated. In FE for teacher's survey, we found that participation is negatively correlated with stress level, and positively correlated with pro-social behaviour.

One can hypothesis that these trends may be largely due to the endogenous choice of participation. Thus, we move on to the next section, which uses the individual participation decisions rather than preschool decisions.

4.4. Individual Participations

Tables 8.5 and 8.6 present the OLS and FE regressions with respect to individual participation as well as participation determined by the preschools. Though insignificant, individual participation is positively significantly correlated with the total difficulties score, but negatively with pro-social behaviour. These correlations are significant especially with emotional symptoms and conduct problems.

Table 8.5: Individual Participation OLS Regressions

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Individual participation	0.490	1.161	0.155	0.559**	0.293	0.369	0.005	0.042	0.037	0.192	0.118	-0.063	-0.022	-0.012	-0.005	-0.018
	(0.594)	(0.728)	(0.231)	(0.245)	(0.197)	(0.261)	(0.228)	(0.285)	(0.163)	(0.192)	(0.248)	(0.313)	(0.024)	(0.026)	(0.027)	(0.033)
Indiv participation numbers	0.241	0.592	0.164	0.409**	0.101	0.099	-0.061	-0.045	0.038	0.129	0.090	-0.068	-0.007	0.005	0.007	-0.010
	(0.368)	(0.466)	(0.163)	(0.176)	(0.117)	(0.171)	(0.136)	(0.178)	(0.099)	(0.123)	(0.137)	(0.190)	(0.016)	(0.016)	(0.017)	(0.021)
Individual participation	0.399	1.099	0.151	0.595**	0.252	0.293	-0.027	0.029	0.023	0.182	0.138	-0.039	-0.024	-0.023	-0.004	-0.011
	(0.593)	(0.744)	(0.233)	(0.252)	(0.198)	(0.264)	(0.229)	(0.292)	(0.163)	(0.195)	(0.250)	(0.318)	(0.024)	(0.027)	(0.027)	(0.034)
Preschool participation	0.806	0.577	0.040	-0.330	0.364	0.690*	0.278	0.128	0.125	0.089	-0.173	-0.223	0.013	0.102**	-0.002	-0.061
	(0.667)	(1.192)	(0.268)	(0.473)	(0.231)	(0.353)	(0.272)	(0.519)	(0.175)	(0.255)	(0.264)	(0.438)	(0.030)	(0.050)	(0.029)	(0.046)
Indiv participation numbers	0.203	0.552	0.166	0.429**	0.078	0.052	-0.074	-0.053	0.034		0.101	-0.057	-0.008	-0.001	0.008	-0.006
	(0.369)	(0.474)	(0.164)	(0.179)	(0.117)	(0.172)	(0.137)	(0.182)	(0.100)	(0.124)	(0.138)	(0.192)	(0.016)	(0.016)	(0.017)	(0.021)
Preschool participation	0.631	0.666	-0.043	-0.325	0.385*	0.757**	0.221	0.136	0.068	0.098	-0.183	-0.184	0.012	0.094*	-0.004	-0.061
	(0.673)	(1.156)	(0.271)	(0.464)	(0.232)	(0.346)	(0.275)	(0.499)	(0.177)	(0.255)	(0.270)	(0.405)	(0.030)	(0.050)	(0.029)	(0.046)
Individual participation	0.494	1.051	0.205	0.572**	0.305	0.345	-0.021	-0.045	0.004	0.179	0.187	0.054	-0.022	-0.015	0.003	-0.013
	(0.600)	(0.736)	(0.241)	(0.246)	(0.204)	(0.265)	(0.234)	(0.289)	(0.166)	(0.192)	(0.258)	(0.316)	(0.025)	(0.027)	(0.028)	(0.033)
Preschool participation ITT	1.032	3.320	0.108	-0.403	0.294	0.712	0.473	2.630**	0.156	0.381	-0.422	-3.538**	0.005	0.098	-0.004	-0.142
	(0.836)	(2.524)	(0.308)	(0.927)	(0.300)	(0.953)	(0.323)	(1.042)	(0.215)	(0.646)	(0.325)	(1.487)	(0.034)	(0.102)	(0.036)	(0.110)
Indiv participation numbers	0.173	0.546	0.174	0.422**	0.093	0.087	-0.095	-0.084	0.001	0.122	0.144	-0.015	-0.008	0.003	0.012	-0.008
	(0.361)	(0.468)	(0.170)	(0.177)	(0.122)	(0.173)	(0.136)	(0.179)	(0.095)	(0.122)	(0.139)	(0.192)	(0.017)	(0.017)	(0.018)	(0.021)
Preschool participation ITT	0.853	2.597	0.002	-0.723	0.329	0.670	0.415	2.226**	0.107	0.424	-0.487	-3.017**	0.007	0.083	-0.008	-0.117
	(0.850)	(2.426)	(0.313)	(0.851)	(0.304)	(0.928)	(0.332)	(1.073)	(0.221)	(0.702)	(0.337)	(1.335)	(0.035)	(0.104)	(0.037)	(0.109)
Control variables	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8.6. Individual Participation FE Regressions

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Individual participation	0.416	1.019	0.130	0.487*	0.333	0.369	-0.069	0.019	0.021	0.145	0.107	-0.062	-0.019	-0.014	-0.016	-0.029
	(0.788)	(0.775)	(0.272)	(0.248)	(0.239)	(0.253)	(0.289)	(0.282)	(0.164)	(0.173)	(0.276)	(0.254)	(0.025)	(0.021)	(0.028)	(0.040)
Indiv participation number	0.242	0.477	0.175	0.360**	0.122	0.087	-0.092	-0.072	0.038	0.102	0.087	-0.053	-0.003	0.004	0.001	-0.014
	(0.452)	(0.443)	(0.190)	(0.127)	(0.125)	(0.167)	(0.180)	(0.194)	(0.068)	(0.077)	(0.127)	(0.134)	(0.018)	(0.010)	(0.019)	(0.030)
Individual participation	0.318	1.005	0.140	0.518**	0.264	0.317	-0.099	0.027	0.013	0.142	0.101	-0.087	-0.021	-0.021	-0.016	-0.025
	(0.816)	(0.774)	(0.290)	(0.242)	(0.244)	(0.268)	(0.299)	(0.281)	(0.168)	(0.175)	(0.284)	(0.267)	(0.026)	(0.022)	(0.027)	(0.038)
Preschool participation	1.049	0.187	-0.098	-0.393	0.736**	0.654	0.322	-0.106	0.089	0.032	0.066	0.313	0.020	0.090**	0.001	-0.049
	(0.923)	(1.247)	(0.449)	(0.484)	(0.291)	(0.505)	(0.408)	(0.444)	(0.200)	(0.214)	(0.381)	(0.405)	(0.040)	(0.041)	(0.032)	(0.046)
Indiv participation number	0.188	0.464	0.181	0.377***	0.082	0.056	-0.109	-0.069	0.033		0.084	-0.066	-0.004	0.000	0.002	-0.012
	(0.477)	(0.455)	(0.202)	(0.121)	(0.130)	(0.179)	(0.188)	(0.198)	(0.069)	(0.076)	(0.131)	(0.141)	(0.019)	(0.010)	(0.018)	(0.029)
Preschool participation	1.069	0.299	-0.131	-0.382	0.784**	0.720	0.337	-0.075	0.079	0.036	0.062	0.312	0.015	0.084*	-0.004	-0.051
	(0.940)	(1.283)	(0.464)	(0.493)	(0.295)	(0.517)	(0.417)	(0.466)	(0.194)	(0.211)	(0.378)	(0.398)	(0.041)	(0.041)	(0.032)	(0.047)
Individual participation	0.450	1.018	0.211	0.515*	0.354	0.374	-0.113	-0.008	-0.002	0.137	0.178	-0.030	-0.020	-0.015	-0.009	-0.028
	(0.869)	(0.794)	(0.285)	(0.249)	(0.263)	(0.258)	(0.307)	(0.292)	(0.183)	(0.174)	(0.300)	(0.260)	(0.026)	(0.021)	(0.030)	(0.041)
Preschool participation IT	2.707***	0.093	-0.702***	1.478***	0.583**	-0.258	2.290***	1.402*	0.535***	0.427	-1.976***	-1.707**	-0.009	0.048	0.001	-0.035
	(0.695)	(1.690)	(0.228)	(0.482)	(0.210)	(0.729)	(0.246)	(0.680)	(0.146)	(0.511)	(0.240)	(0.771)	(0.021)	(0.054)	(0.024)	(0.107)
Indiv participation number	0.206	0.473	0.194	0.371***	0.120	0.087	-0.125	-0.083	0.017	0.098	0.125	-0.039	-0.003	0.003	0.005	-0.014
	(0.483)	(0.451)	(0.197)	(0.127)	(0.134)	(0.171)	(0.187)	(0.197)	(0.072)	(0.076)	(0.133)	(0.136)	(0.019)	(0.010)	(0.020)	(0.031)
Preschool participation IT	2.902***	0.470	-0.689***	1.371***	0.771***	-0.064	2.300***	1.450**	0.520***	0.455	-1.933***	-1.702**	-0.022	0.036	-0.010	-0.045
	(0.387)	(1.611)	(0.157)	(0.441)	(0.107)	(0.709)	(0.150)	(0.660)	(0.058)	(0.518)	(0.107)	(0.742)	(0.015)	(0.052)	(0.016)	(0.103)
Control variables	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. FE also has clustered standard errors at preschool levels.

Since these questions are put to the parents, this may be reflecting the perception of parents: because parents feel that the children have stress, they involve them in the indoor park programmes. Even after controlling for school-wide participation (One preschool did not participate due to an unexpected conflict in scheduling.), the significance remains.

Although the change variables are mostly unreliable, change in total score was positively correlated with the participation variables. As discussed in the balance check section, the ITT variable results are most probably not meaningful.

4.5. Sub-group Analyses

Given the unexpected results, we conducted sub-group analyses, which were not in the original pre-analysis plan. To investigate whether the effect was particularly strong across certain groups, we ran the following regressions, both with OLS and preschool-FE specifications:

$$y_{ij} = \gamma_0 + \gamma_1 Participation_{ij} + \gamma_2 D_{ij} + \gamma_3 Participation_{ij} * D_{ij} + \gamma_4 X_{ij} + f_j + e_{ij}$$

Here, D_{ij} indicates dummies for either of the following variables respectively: frequency of outdoor play, regular indoor facilities usage, whether the preschool is a kindergarten or a nursing school (Dj), and evacuation experience after the disaster.

4.5.1. Outdoor play

Tables 8.7 and 8.8 present the regression with respect to frequency/prohibition of outdoor play. The FE regression has generally more significant coefficients, and the overall trend is consistent between OLS and FE. Overall, the children whose parents never permit them to play outdoors had a positive coefficient between participation and stress level, whereas the children whose parents let them play outdoors had zero or negative coefficients. This trend is consistent across many outcomes—total difficulties, emotional symptoms, peer problems, and pro-social behaviours—and stays the same with inclusion of control variables.

Table 8.7. Outdoor Play OLS Regressions

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	3.378	1.880	1.750**	1.206**	0.420	0.213	0.330	-0.046	0.878**	0.507*	-0.022	0.428*	0.021	0.044	0.074	0.011
	(2.066)	(1.264)	(0.745)	(0.551)	(0.720)	(0.343)	(1.017)	(0.376)	(0.363)	(0.296)	(0.473)	(0.240)	(0.090)	(0.039)	(0.052)	(0.029)
Always permit	1.917	0.603	1.083	0.747	0.181	-0.063	0.181	-0.191	0.472	0.110	0.431	0.832*	-0.023	0.054	0.115*	0.018
	(2.414)	(1.718)	(0.836)	(0.694)	(0.829)	(0.552)	(1.081)	(0.684)	(0.529)	(0.407)	(0.591)	(0.491)	(0.111)	(0.073)	(0.066)	(0.061)
Sometimes permit	-1.060	-0.718	0.612	0.383	-0.789	-0.407	-0.978	-0.727	0.095	0.034	-0.194	0.770*	0.079	0.113*	-0.009	-0.044
	(1.947)	(1.578)	(0.685)	(0.663)	(0.701)	(0.503)	(1.002)	(0.639)	(0.345)	(0.354)	(0.521)	(0.435)	(0.086)	(0.062)	(0.053)	(0.052)
Always*participatio	-5.739**	-2.863**	-2.606***	-1.536***	-0.858	-0.385	-0.944	-0.323	-1.330**	-0.619*	-0.218	-0.485	0.024	-0.044	-0.169**	-0.041
	(2.610)	(1.361)	(0.949)	(0.583)	(0.887)	(0.387)	(1.156)	(0.424)	(0.581)	(0.335)	(0.688)	(0.332)	(0.120)	(0.048)	(0.082)	(0.040)
Sometimes*part.	-1.469	-1.269	-1.768**	-1.040*	0.457	0.027	0.492	0.147	-0.650	-0.403	0.279	-0.563**	-0.018	-0.043	-0.053	-0.006
	(2.178)	(1.309)	(0.819)	(0.574)	(0.764)	(0.360)	(1.077)	(0.395)	(0.418)		(0.613)	(0.274)	(0.096)	(0.041)	(0.069)	(0.032)
With controls																
Participation	2.764	1.543	1.135	1.202**	0.504	0.107	0.133	-0.251	0.992**	0.485	-0.017	0.402	0.059	0.050	0.043	-0.012
	(2.107)	(1.345)	(0.791)	(0.534)	(0.777)	(0.393)	(0.972)	(0.415)	(0.460)	(0.347)	(0.653)	(0.328)	(0.088)	(0.037)	(0.067)	(0.027)
Always permit	0.837	0.006	0.638	0.682	0.001	-0.130	0.077	-0.268	0.120	-0.278	0.665	1.201*	-0.112	-0.042	0.172**	0.059
	(2.243)	(1.872)	(0.857)	(0.708)	(0.795)	(0.639)	(1.035)	(0.794)	(0.566)	(0.478)	(0.734)	(0.632)	(0.110)	(0.085)	(0.084)	(0.071)
Sometimes permit	-1.184	-1.524	0.562	0.572	-0.758	-0.537	-0.989	-1.198*	-0.000	-0.361	-0.057	1.166**	0.029	0.078	0.017	-0.034
	(1.955)	(1.733)	(0.700)	(0.662)	(0.691)	(0.577)	(0.952)	(0.712)	(0.375)	(0.378)	(0.633)	(0.538)	(0.079)	(0.064)	(0.070)	(0.054)
Always*participatio	-4.329*	-2.277	-1.712*	-1.177**	-0.556	-0.303	-0.729	-0.246	-1.332**	-0.551	-0.015	-0.433	0.026	-0.036	-0.176*	-0.029
	(2.382)	(1.385)	(0.969)	(0.548)	(0.856)	(0.435)	(1.100)	(0.494)	(0.626)	(0.374)	(0.833)	(0.447)	(0.119)	(0.052)	(0.096)	(0.044)
Sometimes*part.	-1.698	-0.744	-1.560*	-0.991*	0.459	0.142	0.378	0.436	-0.974**	-0.331	0.356	-0.736**	-0.011	-0.048	-0.041	0.017
	(2.175)	(1.351)	(0.852)	(0.556)	(0.778)	(0.409)	(1.025)	(0.434)	(0.487)	(0.342)	(0.734)	(0.347)	(0.089)	(0.039)	(0.083)	(0.030)
Participation variabl	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The omitted dummy is "never permit" children to play outside.

Table 8.8: Outdoor Play FE Regressions

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	3.468**	2.071**	1.643**	1.299***	0.597	0.303	0.336	-0.065	0.892***	0.534***	0.232	0.492**	0.019	0.035	0.083	0.014
	(1.291)	(0.747)	(0.718)	(0.259)	(0.682)	(0.297)	(0.582)	(0.308)	(0.248)	(0.114)	(0.517)	(0.236)	(0.120)	(0.051)	(0.056)	(0.028)
Always permit	1.793*	0.696	0.965*	0.744	0.193	0.036	0.223	-0.144	0.412	0.060	0.415	0.880	-0.028	0.045	0.134*	0.021
	(1.016)	(1.038)	(0.559)	(0.524)	(0.369)	(0.435)	(0.717)	(0.646)	(0.453)	(0.331)	(0.411)	(0.730)	(0.104)	(0.101)	(0.071)	(0.051)
Sometimes permit	-0.874	-0.641	0.560	0.366	-0.671	-0.287	-0.830*	-0.689	0.067	-0.031	-0.141	0.865*	0.080	0.113	-0.011	-0.049
	(1.254)	(1.244)	(0.450)	(0.463)	(0.716)	(0.535)	(0.460)	(0.591)	(0.268)	(0.228)	(0.413)	(0.475)	(0.109)	(0.078)	(0.035)	(0.043)
Always*participation	-6.114***	-3.311***	-2.686***	-1.666***	-0.876	-0.484	-1.047	-0.418	-1.506**	-0.743***	-0.041	-0.431	0.036	-0.033	-0.203*	-0.050
	(1.410)	(0.824)	(0.757)	(0.245)	(0.514)	(0.349)	(0.858)	(0.400)	(0.542)	(0.225)	(0.543)	(0.335)	(0.114)	(0.064)	(0.105)	(0.047)
Sometimes*part.	-2.142	-1.622*	-1.891***	-1.123***	0.305	-0.101	0.256	0.073	-0.812**	-0.471***	0.384	-0.542**	-0.011	-0.038	-0.062	-0.008
	(1.533)	(0.861)	(0.665)	(0.303)	(0.753)	(0.282)	(0.601)	(0.332)	(0.333)		(0.400)	(0.206)	(0.117)	(0.047)	(0.066)	(0.031)
With controls																
Participation	2.317**	1.423	1.056	1.170***	0.394	0.084	-0.027	-0.284	0.893***	0.453**	0.358	0.482**	0.046	0.044	0.053	-0.015
	(1.085)	(0.899)	(0.629)	(0.294)	(0.668)	(0.348)	(0.663)	(0.347)	(0.305)	(0.174)	(0.402)	(0.187)	(0.119)	(0.044)	(0.063)	(0.029)
Always permit	0.458	-0.290	0.582	0.624	-0.152	-0.249	0.002	-0.286	0.027	-0.379	0.746*	1.285**	-0.119	-0.053	0.165	0.047
	(1.016)	(1.266)	(1.040)	(0.738)	(0.466)	(0.609)	(0.677)	(0.685)	(0.431)	(0.301)	(0.364)	(0.614)	(0.105)	(0.112)	(0.104)	(0.047)
Sometimes permit	-1.389	-1.514	0.529	0.546	-0.839	-0.537	-1.035**	-1.154**	-0.044	-0.368	-0.027	1.163***	0.027	0.074	0.012	-0.041
	(1.453)	(1.437)	(0.578)	(0.546)	(0.779)	(0.676)	(0.471)	(0.513)	(0.324)	(0.220)	(0.393)	(0.359)	(0.110)	(0.098)	(0.044)	(0.035)
Always*participation	-4.323***	-2.274*	-1.787	-1.201***	-0.499	-0.281	-0.717	-0.262	-1.318**	-0.529**	-0.057	-0.496	0.030	-0.030	-0.183	-0.031
	(1.269)	(1.100)	(1.098)	(0.369)	(0.568)	(0.490)	(0.770)	(0.481)	(0.501)	(0.247)	(0.462)	(0.375)	(0.108)	(0.059)	(0.108)	(0.045)
Sometimes*part.	-1.501	-0.797	-1.537**	-0.982***	0.523	0.114	0.438	0.398	-0.924**	-0.327**	0.333	-0.718***	-0.010	-0.046	-0.043	0.019
	(1.570)	(0.870)	(0.690)	(0.297)	(0.801)	(0.300)	(0.761)	(0.348)	(0.342)	(0.154)	(0.417)	(0.226)	(0.107)	(0.050)	(0.065)	(0.036)
Participation variable	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The omitted dummy is "never permit" children to play outside. FE also has clustered standard errors at preschool levels.

4.5.2. Regular indoor play at PEP Kids

PEP Kids is the regular indoor play facility in Koriyama city. Tables 8.9 and 8.10 present the regression with respect to frequency of PEP Kids, which is largely considered to be an alternative to outdoor play. Although the PEP Kids and outdoor play variables themselves are not significantly correlated, we observe that the positive correlation is concentrated among those who regularly (at least once a week) use PEP Kids although they have lower stress levels without participation. This is true with total difficulties, conduct problems, hyperactivities, and peer problems.

Table 8.9: PEP Kids OLS Regressions

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	1.223	-0.905	0.527	0.179	0.440	-0.287	-0.027	-0.563*	0.282	-0.234*	-0.926	0.328	0.095	0.063**	-0.030	-0.011
	(1.039)	(0.752)	(0.550)	(0.377)	(0.395)	(0.174)	(0.606)	(0.311)	(0.283)	(0.135)	(0.667)	(0.327)	(0.086)	(0.031)	(0.071)	(0.029)
Almost every week	-2.231*	-3.575**	0.821	-0.306	0.000	-0.022	-2.000*	-1.751**	-1.051***	-1.496***	-1.179	0.387	0.190**	0.064	-0.108*	-0.111*
	(1.168)	(1.588)	(1.523)	(0.999)	(0.347)	(0.653)	(1.097)	(0.757)	(0.360)	(0.304)	(1.166)	(0.751)	(0.084)	(0.077)	(0.064)	(0.063)
Sometimes	-0.156	-2.360**	0.179	-0.489	0.025	-0.547*	-0.575	-0.881*	0.215	-0.443*	-0.821	0.674	0.084	0.087*	-0.031	-0.032
	(1.219)	(1.004)	(0.568)	(0.472)	(0.456)	(0.313)	(0.645)	(0.452)	(0.328)	(0.237)	(0.677)	(0.454)	(0.090)	(0.051)	(0.074)	(0.050)
Every week*part.	5.111**	3.768***	-0.727	0.269	1.360**	0.802***	2.893**	1.535***	1.585***	1.163***	0.459	-0.808**	-0.196*	-0.046	0.004	0.008
	(2.154)	(0.982)	(1.677)	(0.542)	(0.626)	(0.297)	(1.240)	(0.444)	(0.557)	(0.169)	(1.291)	(0.402)	(0.102)	(0.037)	(0.100)	(0.033)
Sometimes*part.	-1.313	1.033	-0.878	-0.096	-0.174	0.397**	0.156	0.452	-0.417	0.281*	1.265*	-0.347	-0.098	-0.077**	0.029	0.022
	(1.402)	(0.810)	(0.650)	(0.401)	(0.504)	(0.201)	(0.706)	(0.330)	(0.375)		(0.732)	(0.345)	(0.094)	(0.034)	(0.081)	(0.032)
With controls																
Participation	-0.008	-0.798	-0.289	0.137	0.503	-0.322*	-0.423	-0.475	0.202	-0.137	-1.073*	0.054	0.167*	0.068**	-0.073	-0.029
	(1.380)	(0.842)	(0.603)	(0.438)	(0.558)	(0.191)	(0.725)	(0.346)	(0.361)	(0.155)	(0.626)	(0.302)	(0.093)	(0.033)	(0.089)	(0.032)
Almost every week	-2.697*	-5.020**	0.239	-0.690	-0.190	-0.466	-1.998	-2.433*	-0.747*	-1.431***	-2.931***	-0.473	0.142	0.004	-0.153	-0.162*
	(1.455)	(2.128)	(1.519)	(1.198)	(0.610)	(0.880)	(1.548)	(1.264)	(0.431)	(0.460)	(0.741)	(1.052)	(0.096)	(0.113)	(0.101)	(0.089)
Sometimes	-0.994	-2.611**	-0.514	-0.904*	-0.064	-0.602*	-0.628	-0.702	0.211	-0.402	-1.290**	0.398	0.125	0.093*	-0.069	-0.058
	(1.219)	(1.094)	(0.566)	(0.523)	(0.519)	(0.360)	(0.721)	(0.513)	(0.378)	(0.269)	(0.612)	(0.468)	(0.095)	(0.055)	(0.092)	(0.058)
Every week*part.	5.469**	4.866***	-0.027	0.446	1.456*	1.181***	2.788*	2.036***	1.251**	1.203***	2.315**	-0.276	-0.230**	-0.055	0.062	0.045
	(2.120)	(1.345)	(1.581)	(0.737)	(0.836)	(0.451)	(1.670)	(0.708)	(0.513)	(0.275)	(0.893)	(0.605)	(0.117)	(0.066)	(0.130)	(0.070)
Sometimes*part.	0.039	1.355	-0.020	0.222	-0.082	0.431*	0.466	0.410	-0.325	0.291	1.639**	-0.196	-0.122	-0.066*	0.052	0.028
	(1.422)	(0.868)	(0.641)	(0.444)	(0.565)	(0.225)	(0.784)	(0.368)	(0.428)	(0.181)	(0.683)	(0.333)	(0.097)	(0.037)	(0.098)	(0.036)
Participation variable	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The omitted dummy is "almost never" use the PEP Kids indoor facilities.

Table 8.10. PEP Kids FE Regressions

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	0.345	-0.814	0.299	0.265	0.348	-0.270*	-0.366	-0.594*	0.065	-0.215	-0.530	0.390	0.090	0.061**	-0.014	-0.011
	(1.033)	(0.878)	(0.832)	(0.495)	(0.324)	(0.143)	(0.603)	(0.291)	(0.361)	(0.195)	(0.455)	(0.276)	(0.071)	(0.025)	(0.064)	(0.030)
Almost every week	-4.040**	-3.681**	0.591	-0.477	-0.636	-0.104	-2.864***	-1.810***	-1.132**	-1.291***	-0.984	0.150	0.179***	0.070	-0.059	-0.109**
	(1.919)	(1.323)	(0.984)	(0.720)	(0.446)	(0.629)	(0.516)	(0.646)	(0.425)	(0.309)	(1.500)	(0.954)	(0.060)	(0.067)	(0.046)	(0.044)
Sometimes	-0.491	-2.072*	0.108	-0.527	-0.060	-0.440	-0.738	-0.801*	0.198	-0.304	-0.816*	0.624	0.078	0.085*	-0.017	-0.033
	(1.277)	(1.055)	(0.776)	(0.595)	(0.459)	(0.366)	(0.522)	(0.394)	(0.515)	(0.359)	(0.401)	(0.535)	(0.062)	(0.048)	(0.048)	(0.038)
Every week*part.	7.171**	3.771***	-0.481	0.283	2.095**	0.869**	3.802***	1.545***	1.754**	1.073***	0.272	-0.658	-0.206**	-0.059	-0.033	0.016
	(3.030)	(0.976)	(1.364)	(0.562)	(0.873)	(0.315)	(0.745)	(0.397)	(0.648)	(0.223)	(1.571)	(0.526)	(0.079)	(0.041)	(0.058)	(0.032)
Sometimes*part.	-0.896	0.918	-0.917	-0.134	-0.025	0.367	0.360	0.434	-0.314	0.251	1.242***	-0.332	-0.089	-0.074**	0.012	0.021
	(1.470)	(0.850)	(0.899)	(0.445)	(0.512)	(0.218)	(0.457)	(0.297)	(0.597)		(0.377)	(0.347)	(0.060)	(0.034)	(0.059)	(0.028)
With controls																
Participation	-0.581	-0.988	-0.386	0.100	0.336	-0.379*	-0.623	-0.529	0.093	-0.179	-0.642*	0.140	0.152	0.063*	-0.071	-0.033
	(1.223)	(0.987)	(0.881)	(0.538)	(0.472)	(0.195)	(0.799)	(0.343)	(0.307)	(0.201)	(0.348)	(0.332)	(0.096)	(0.036)	(0.081)	(0.035)
Almost every week	-3.242***	-5.012**	0.112	-0.759	-0.372	-0.463	-2.137**	-2.302***	-0.844*	-1.488**	-2.865***	-0.650	0.139	0.005	-0.168**	-0.181**
	(1.129)	(1.955)	(0.637)	(0.895)	(0.420)	(0.554)	(0.756)	(0.625)	(0.465)	(0.545)	(0.653)	(1.528)	(0.089)	(0.093)	(0.070)	(0.074)
Sometimes	-1.383	-2.642**	-0.597	-0.942*	-0.194	-0.605	-0.756	-0.674	0.164	-0.421	-1.147***	0.375	0.121	0.091	-0.074	-0.065
	(0.866)	(0.987)	(0.699)	(0.525)	(0.383)	(0.444)	(0.926)	(0.487)	(0.338)	(0.293)	(0.327)	(0.632)	(0.086)	(0.056)	(0.061)	(0.039)
Every week*part.	6.010***	4.908***	0.032	0.475	1.681*	1.206***	2.968***	1.992***	1.328**	1.234***	2.258***	-0.186	-0.231***	-0.057	0.072	0.054
	(1.801)	(1.543)	(0.899)	(0.763)	(0.851)	(0.394)	(0.874)	(0.356)	(0.539)	(0.363)	(0.609)	(0.856)	(0.073)	(0.065)	(0.092)	(0.053)
Sometimes*part.	0.339	1.399	-0.019	0.222	0.070	0.459	0.560	0.405	-0.271	0.313	1.523***	-0.217	-0.117	-0.063	0.055	0.030
	(1.060)	(0.947)	(0.809)	(0.553)	(0.429)	(0.270)	(0.861)	(0.354)	(0.425)	(0.213)	(0.309)	(0.408)	(0.087)	(0.037)	(0.077)	(0.032)
Participation variable	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The omitted dummy is "almost never" use the PEP Kids indoor facilities. FE also has clustered standard errors at preschool levels.

4.5.3. Kindergarten and nursing schools

Table 8.11 presents the OLS regression with parents' survey.[13] The coefficients are significant mostly with and without controls, and for all outcome variables, indicate that (i) among children in the nursing schools, participation is positively correlated with their stress levels; (ii) with no participation, children in the kindergartens have higher stress levels; and (iii) among children in the kindergartens, participation is not correlated with stress levels. Table 8.12 presents the OLS regression with the teachers' survey, with less consistent coefficients compared to the parents' survey. For the ones that are significant (e.g., total difficulties), they indicate almost exactly the opposite results: (i) among children in the nursing schools, participation is negatively correlated with stress levels; (ii) with no participation, children in the kindergartens have lower stress levels; and (iii) among children in the kindergartens, participation is slightly negatively correlated with stress levels. As discussed above in the Data section, this is possible only if parents and teachers are looking at different aspects of children's psychological conditions.

One possible explanation is that the children in the nursing schools were energised by the indoor park only with respect to their time at the nursing schools, but became tired at home so that, from the parents' perspective, the impact appeared negative. Such impact was not seen among children in the kindergartens.

[13] Note that there is no preschool-FE regression because the kindergarten dummy is a preschool level variable.

Table 8.11. Kindergarten Regressions with Parents' Survey

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	2.205**	1.167**	0.397	0.109	0.952***	0.476***	0.458	0.261	0.397*	0.321**	-0.735**	-0.385**	0.068	-0.004	-0.052	-0.015
	(0.944)	(0.492)	(0.354)	(0.186)	(0.262)	(0.139)	(0.531)	(0.194)	(0.231)	(0.127)	(0.338)	(0.191)	(0.054)	(0.025)	(0.053)	(0.024)
Kindergarten	3.104**	2.536***	0.974**	0.239	0.874**	0.781***	0.499	0.742*	0.757**	0.775***	-1.116**	-0.798**	0.079	-0.006	-0.064	-0.037
	(1.213)	(0.910)	(0.487)	(0.366)	(0.384)	(0.292)	(0.605)	(0.384)	(0.315)	(0.247)	(0.447)	(0.357)	(0.064)	(0.042)	(0.062)	(0.044)
Kindergarten*part.	-2.350*	-1.343**	-0.722	0.064	-0.906**	-0.555***	-0.289	-0.535**	-0.433	-0.317**	1.237**	0.580***	-0.089	0.005	0.073	0.030
	(1.331)	(0.596)	(0.534)	(0.251)	(0.423)	(0.174)	(0.645)	(0.229)	(0.350)	(0.156)	(0.499)	(0.220)	(0.068)	(0.027)	(0.067)	(0.027)
With controls																
Participation	1.212	1.549**	-0.002	0.239	0.769*	0.751***	0.038	0.323	0.407	0.236	-1.050**	-0.666**	0.128*	0.017	-0.070	-0.045
	(1.570)	(0.762)	(0.575)	(0.254)	(0.429)	(0.263)	(0.716)	(0.300)	(0.320)	(0.178)	(0.506)	(0.321)	(0.067)	(0.029)	(0.069)	(0.035)
Kindergarten	5.133	13.660**	1.295	2.656	1.434	4.375**	1.149	5.526**	1.255		-1.654	-5.000	0.337	0.349	-0.544***	-0.792***
	(4.450)	(5.958)	(1.956)	(2.428)	(1.486)	(2.021)	(1.805)	(2.599)	(1.414)	(1.659)	(2.443)	(3.350)	(0.232)	(0.273)	(0.188)	(0.252)
Kindergarten*part.	-1.362	-1.497*	-0.445	0.100	-0.336	-0.918***	0.072	-0.549	-0.653	-0.129	2.151***	0.747**	-0.118	-0.008	0.058	0.049
	(2.146)	(0.866)	(0.862)	(0.314)	(0.665)	(0.300)	(0.864)	(0.345)	(0.487)	(0.219)	(0.694)	(0.362)	(0.088)	(0.035)	(0.088)	(0.040)
Participation variable	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The omitted dummy is "almost never" use the PEP Kids indoor facilities.

Table 8.12: Kindergarten Regressions with Teachers' Survey

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	-4.285	1.231	-0.581	0.075	-0.329	1.097*	-2.703*	-0.366	-0.674	0.431	0.151	0.890	0.269*	0.170***	0.012	-0.009
	(3.934)	(1.974)	(0.368)	(0.387)	(1.429)	(0.585)	(1.438)	(0.946)	(0.723)	(0.585)	(0.745)	(0.707)	(0.138)	(0.050)	(0.073)	(0.029)
Kindergarten	-5.694	-0.506	-0.778*	-0.188	-0.639	0.977	-3.333**	-1.447	-0.944	0.195	1.368*	1.470	-0.042	-0.047	0.293***	0.225***
	(3.979)	(2.299)	(0.400)	(0.467)	(1.448)	(0.699)	(1.471)	(1.134)	(0.740)	(0.682)	(0.789)	(0.937)	(0.150)	(0.084)	(0.094)	(0.063)
Kindergarten*part.	3.727	-1.638	0.708	-0.120	0.129	-1.221**	2.413	0.271	0.555	-0.548	0.068	-0.688	-0.040	0.002	-0.225**	-0.126**
	(4.026)	(2.039)	(0.431)	(0.409)	(1.462)	(0.616)	(1.505)	(0.991)	(0.762)	(0.609)	(0.850)	(0.762)	(0.153)	(0.065)	(0.098)	(0.054)
With controls																
Participation	10.068**	-1.456	-1.213***	-0.748	-2.682***	0.471	-4.907***	-0.884	-1.204**	-0.243	2.566***	1.092	-0.001	-0.010	0.073	0.065
	(1.570)	(2.184)	(0.413)	(0.483)	(0.492)	(0.735)	(0.795)	(1.083)	(0.508)	(0.682)	(0.862)	(0.817)	(0.126)	(0.048)	(0.119)	(0.052)
Kindergarten	-0.195	8.895*	2.180*	3.972***	-0.622	1.536	-3.137	-0.394	1.402		5.404**	3.825	0.543***	0.636***	0.172	-0.139
	(4.829)	(5.308)	(1.186)	(1.270)	(1.420)	(1.743)	(2.370)	(2.345)	(1.608)	(1.526)	(2.517)	(3.207)	(0.149)	(0.122)	(0.183)	(0.154)
Kindergarten*part.	6.079***	1.269	1.027**	0.425	1.440**	-0.454	3.121***	1.058	0.632	0.104	0.644	-0.153	-0.119	0.047	-0.275*	-0.097
	(2.008)	(2.318)	(0.481)	(0.504)	(0.572)	(0.761)	(1.096)	(1.147)	(0.670)	(0.732)	(0.973)	(0.887)	(0.139)	(0.052)	(0.143)	(0.063)
Participation variable	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The omitted dummy is "almost never" use the PEP Kids indoor facilities.

4.5.4. Evacuation experience

Intuitively, we expected that the indoor park treatment effect might be different between those who have experienced evacuation and those who have not. Tables 8.13 and 8.14 present the OLS and FE regression results. However, we observe that the interaction term (y3) is mostly not significant in both cases. The only significant coefficient was the FE regression on the peer problems, where evacuation implied significantly positive correlation between stress level and participation. (At the same time, the standard deviation is too small because this method of analysis causes the problem of alpha inflation.) Therefore, the treatment effect was about the same for those who did and who did not experience evacuation.

Table 8.13: Evacuation OLS Regressions

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	0.396	0.028	0.110	0.124	0.417	0.085	0.059	-0.145	-0.190	-0.035	0.250	0.101	0.047	0.001	0.002	0.009
	(0.708)	(0.325)	(0.298)	(0.153)	(0.273)	(0.120)	(0.346)	(0.134)	(0.229)	(0.089)	(0.337)	(0.152)	(0.045)	(0.020)	(0.039)	(0.019)
Evacuation	1.286	0.764	1.182**	0.622	0.435	0.161	-0.036	0.093	-0.295	-0.112	0.577	0.482	0.112**	0.038	0.018	0.014
	(1.588)	(1.012)	(0.600)	(0.404)	(0.495)	(0.317)	(0.622)	(0.409)	(0.369)	(0.250)	(0.514)	(0.363)	(0.055)	(0.037)	(0.064)	(0.045)
Evacuation*part.	0.243	0.499	-0.697	-0.047	-0.140	0.088	0.410	0.165	0.671*	0.293*	-0.572	-0.315	-0.094	-0.005	-0.027	-0.016
	(1.690)	(0.649)	(0.645)	(0.274)	(0.530)	(0.195)	(0.666)	(0.251)	(0.403)	(0.165)	(0.567)	(0.223)	(0.060)	(0.024)	(0.069)	(0.027)
With controls																
Participation	0.744	0.340	0.164	0.335*	0.695*	0.056	0.017	-0.086	-0.132	0.034	0.319	-0.022	0.104*	0.014	-0.039	-0.003
	(1.080)	(0.491)	(0.411)	(0.199)	(0.390)	(0.181)	(0.484)	(0.178)	(0.266)	(0.120)	(0.416)	(0.193)	(0.053)	(0.019)	(0.050)	(0.023)
Evacuation	1.527	-0.045	1.562***	0.516	0.287	-0.234	-0.101	-0.089	-0.220		0.548	0.641	0.113*	0.014	0.013	0.044
	(1.419)	(1.077)	(0.602)	(0.422)	(0.436)	(0.375)	(0.650)	(0.487)	(0.381)	(0.267)	(0.564)	(0.430)	(0.068)	(0.043)	(0.077)	(0.053)
Evacuation*part.	-0.883	0.448	-1.196*	-0.072	-0.335	0.141	0.176	0.064	0.472	0.315*	-0.398	-0.336	-0.122*	-0.006	0.005	-0.021
	(1.557)	(0.688)	(0.654)	(0.279)	(0.486)	(0.259)	(0.710)	(0.311)	(0.423)	(0.180)	(0.636)	(0.286)	(0.071)	(0.028)	(0.082)	(0.032)
Participation variable	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8.14: Evacuation FE Regressions

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	0.192	0.016	-0.077	0.166	0.512	0.069	0.053	-0.173	-0.297	-0.047	0.502	0.168	0.049	-0.000	-0.003	0.009
	(0.901)	(0.403)	(0.377)	(0.188)	(0.350)	(0.151)	(0.376)	(0.189)	(0.224)	(0.069)	(0.555)	(0.141)	(0.043)	(0.019)	(0.042)	(0.016)
Evacuation	1.259	0.569	1.245	0.574	0.302	0.025	0.063	0.119	-0.351	-0.149	0.706*	0.693*	0.102*	0.020	0.033	0.036
	(1.432)	(0.906)	(0.754)	(0.573)	(0.333)	(0.336)	(0.486)	(0.336)	(0.221)	(0.190)	(0.381)	(0.346)	(0.056)	(0.041)	(0.042)	(0.039)
Evacuation*part.	0.087	0.535	-0.820	-0.043	-0.040	0.158	0.253	0.124	0.694***	0.296***	-0.512	-0.338**	-0.099	-0.002	-0.025	-0.020
	(1.417)	(0.516)	(0.695)	(0.291)	(0.379)	(0.185)	(0.503)	(0.206)	(0.203)	(0.098)	(0.451)	(0.161)	(0.062)	(0.022)	(0.062)	(0.016)
With controls																
Participation	0.332	0.162	0.077	0.300*	0.600	0.007	-0.132	-0.156	-0.213	0.012	0.654*	0.057	0.092**	0.011	-0.033	-0.005
	(1.213)	(0.477)	(0.485)	(0.155)	(0.474)	(0.215)	(0.418)	(0.235)	(0.215)	(0.082)	(0.370)	(0.138)	(0.042)	(0.015)	(0.056)	(0.026)
Evacuation	1.349	-0.027	1.543**	0.509	0.233	-0.224	-0.202	-0.108	-0.225		0.579	0.663	0.117*	0.016	0.014	0.043
	(1.291)	(1.215)	(0.551)	(0.596)	(0.350)	(0.481)	(0.607)	(0.381)	(0.310)	(0.246)	(0.483)	(0.404)	(0.061)	(0.050)	(0.030)	(0.033)
Evacuation*part.	-0.702	0.504	-1.250*	-0.086	-0.219	0.185	0.258	0.094	0.509	0.311***	-0.368	-0.369	-0.127*	-0.007	0.008	-0.021
	(1.557)	(0.511)	(0.672)	(0.275)	(0.463)	(0.231)	(0.629)	(0.212)	(0.302)	(0.094)	(0.511)	(0.233)	(0.066)	(0.029)	(0.051)	(0.016)
Participation variable	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. FE also has clustered standard errors at preschool levels.

4.6. Heterogeneities across response time

In the pre-analysis plan, we wrote that we would omit the kindergartens with overlapping participation and questionnaire periods. In fact, there were no such preschools since the question asked about the situation in the past 30 days, and all preschools are included. However, about half of the respondents responded within less than two weeks after participation, making their response 'too early' relative to the intended times. Dropping all of them may have been significantly restrictive in terms of sample size, so instead we interacted to see whether the estimates differed importantly along the response time spectrum.

Tables 8.15 and 8.16 present the regressions from parents' surveys, and tables 8.17 and 8.18 present the ones from teachers' surveys. To get an overall picture, we divided the samples into two groups: early respondents (earlier than median) and late respondents (later than median[14]) Overall, we did not find that the response time significantly alters the regression coefficients. (For one kindergarten that did not participate at all, we assigned 'late' to all the responses because their responses were mostly concentrated in the late part of the response time spectrum.) Table 18 shows many statistically significant

[14] Median was 12 days for parents, and 19 days for teachers.

coefficients, but the round numbers indicate that these are driven only by one sample. And these coefficients go away when the control variables are added.

Table 8.15: Early OLS Regressions in Parents' Survey

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	0.853	0.417	-0.124	-0.075	0.413	0.143	0.338	0.123	0.226	0.225*	-0.117	-0.109	-0.000	-0.033	0.013	0.011
	(0.852)	(0.459)	(0.318)	(0.169)	(0.290)	(0.128)	(0.346)	(0.179)	(0.228)	(0.123)	(0.329)	(0.163)	(0.038)	(0.022)	(0.038)	(0.020)
Early	0.649	-0.286	0.021	-0.665*	-0.506	-0.296	0.517	0.500	0.617**	0.176	-0.334	-0.019	-0.083	-0.103**	0.050	0.001
	(1.363)	(0.905)	(0.791)	(0.377)	(0.365)	(0.291)	(0.713)	(0.377)	(0.286)	(0.236)	(0.504)	(0.348)	(0.079)	(0.040)	(0.067)	(0.042)
Early*part.	-1.092	-0.311	-0.012	0.410	0.235	-0.014	-0.557	-0.423*	-0.759**	-0.284*	0.542	0.176	0.079	0.070***	-0.073	-0.014
	(1.468)	(0.604)	(0.820)	(0.257)	(0.406)	(0.183)	(0.747)	(0.232)	(0.323)	(0.155)	(0.551)	(0.222)	(0.082)	(0.026)	(0.072)	(0.026)
With controls																
Participation	0.449	0.805	-0.203	0.198	0.255	0.032	0.196	0.241	0.201	0.334*	0.384	-0.159	0.041	0.000	-0.006	-0.009
	(1.168)	(0.699)	(0.402)	(0.234)	(0.412)	(0.225)	(0.489)	(0.281)	(0.290)	(0.192)	(0.431)	(0.268)	(0.048)	(0.023)	(0.046)	(0.026)
Early	-0.244	-0.692	0.172	-0.721	-1.255*	-0.628	0.042	0.202	0.798*		0.612	0.132	-0.092	-0.061	0.018	-0.081
	(2.378)	(1.422)	(1.133)	(0.499)	(0.643)	(0.458)	(0.936)	(0.604)	(0.470)	(0.388)	(0.796)	(0.534)	(0.094)	(0.057)	(0.101)	(0.063)
Early*part.	-0.687	-0.412	-0.351	0.252	0.890	0.104	-0.532	-0.452	-0.693	-0.315	-0.487	0.052	0.086	0.025	-0.088	0.014
	(2.417)	(0.802)	(1.151)	(0.302)	(0.658)	(0.274)	(0.959)	(0.329)	(0.464)	(0.225)	(0.825)	(0.324)	(0.092)	(0.029)	(0.108)	(0.031)
Participation variable	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8.16: Early FE Regressions in Parents' Survey

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	0.234	0.274	-0.402	-0.147	0.351	0.109	0.179	0.077	0.106	0.234	0.389	0.025	-0.004	-0.053**	0.003	0.012
	(1.342)	(0.584)	(0.389)	(0.186)	(0.411)	(0.167)	(0.392)	(0.248)	(0.320)	(0.145)	(0.587)	(0.250)	(0.038)	(0.023)	(0.030)	(0.023)
Early	-1.065	-0.948	-0.399	-1.011**	-1.028**	-0.669	-0.440	0.062	0.802	0.671*	0.257	0.183	-0.099	-0.187***	-0.003	-0.018
	(2.001)	(1.314)	(1.128)	(0.454)	(0.438)	(0.477)	(0.662)	(0.491)	(0.481)	(0.348)	(0.892)	(0.657)	(0.099)	(0.043)	(0.071)	(0.055)
Early*part.	0.201	-0.030	0.245	0.544**	0.571	0.066	-0.030	-0.335	-0.585	-0.305*	-0.121	0.050	0.056	0.091***	-0.036	-0.014
	(1.927)	(0.577)	(0.921)	(0.224)	(0.459)	(0.202)	(0.838)	(0.214)	(0.405)	(0.173)	(0.810)	(0.284)	(0.104)	(0.025)	(0.062)	(0.029)
With controls																
Participation	-0.069	0.585	-0.347	0.099	0.155	-0.003	-0.017	0.166	0.140	0.323	0.860*	-0.037	0.028	-0.006	0.003	-0.014
	(1.053)	(0.654)	(0.439)	(0.198)	(0.419)	(0.224)	(0.256)	(0.240)	(0.263)	(0.197)	(0.442)	(0.372)	(0.048)	(0.029)	(0.047)	(0.038)
Early	-0.219	-0.244	0.090	-0.919*	-1.157**	-0.373	-0.173	0.330	1.021*		0.803	0.011	-0.091	-0.073*	0.026	-0.089
	(2.382)	(1.645)	(1.467)	(0.452)	(0.540)	(0.582)	(0.698)	(0.657)	(0.508)	(0.447)	(0.805)	(0.746)	(0.118)	(0.040)	(0.088)	(0.053)
Early*part.	-0.067	-0.360	-0.171	0.352	1.014*	0.078	-0.209	-0.434	-0.702	-0.355	-0.894	-0.003	0.088	0.030	-0.096	0.019
	(2.467)	(0.823)	(1.276)	(0.262)	(0.538)	(0.278)	(0.967)	(0.343)	(0.410)	(0.235)	(0.744)	(0.376)	(0.122)	(0.031)	(0.091)	(0.036)
Participation variable	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. FE also has clustered standard errors at preschool levels.

Table 8.17: Early OLS Regressions in Teachers' Survey

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	0.039	-0.186	0.148	0.020	-0.094	-0.153	-0.020	-0.004	0.003	-0.047	-0.453	0.143	0.329***	0.213***	0.254***	0.161***
	(0.891)	(0.567)	(0.216)	(0.139)	(0.313)	(0.208)	(0.462)	(0.314)	(0.241)	(0.177)	(0.397)	(0.279)	(0.061)	(0.045)	(0.059)	(0.046)
Early	-0.838	-1.845	0.257	-0.119	-1.152***	-1.277**	-0.190	-0.179	0.248	-0.209	-2.126**	-1.855**	0.350***	0.098	-0.157	-0.108
	(1.651)	(1.785)	(0.510)	(0.405)	(0.394)	(0.537)	(0.832)	(0.872)	(0.753)	(0.575)	(1.043)	(0.778)	(0.066)	(0.068)	(0.105)	(0.073)
Early*part.	1.389	2.261	-0.255	0.132	1.333***	1.356***	0.406	0.366	-0.067	0.381	1.500	0.954	-0.403***	-0.116**	0.207*	0.130**
	(1.765)	(1.681)	(0.532)	(0.375)	(0.442)	(0.500)	(0.892)	(0.818)	(0.776)	(0.553)	(1.094)	(0.707)	(0.071)	(0.056)	(0.108)	(0.065)
With controls																
Participation	-10.162***	-0.542	-0.245	-0.285	-3.404***	-0.266	-5.155***	-0.098	-1.293	0.042	4.432**	0.666	-0.054	0.037	-0.057	-0.025
	(3.280)	(1.112)	(1.007)	(0.242)	(0.934)	(0.358)	(1.659)	(0.627)	(1.073)	(0.322)	(1.785)	(0.493)	(0.110)	(0.030)	(0.110)	(0.042)
Early	-8.185*	1.291	0.236	0.578	-3.160***	-0.683	-5.045**	0.044	-0.301	1.551**	0.781	-2.873**	0.002	-0.019	0.117	0.061
	(4.576)	(2.359)	(1.191)	(0.622)	(0.908)	(0.666)	(2.136)	(1.238)	(1.695)	(0.776)	(2.431)	(1.152)	(0.107)	(0.072)	(0.198)	(0.095)
Early*part.	9.547**	-0.350	-0.214	-0.429	3.692***	0.906	5.349**	-0.018	0.957	-0.817	-2.089	1.385	-0.019	-0.023	-0.033	0.033
	(4.744)	(1.974)	(1.259)	(0.469)	(0.980)	(0.575)	(2.230)	(1.018)	(1.723)	(0.662)	(2.502)	(0.922)	(0.114)	(0.052)	(0.203)	(0.076)
Participation variable:	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8.18: Early FE Regressions in Teachers' Survey

	Total Difficulties		Emotional symptoms		Conduct problems		Hyperactivity /inattention		Peer problems		Prosocial behaviors		Change in total score		Change in prosocial behaviors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Without controls																
Participation	-12.000***	0.457	1.000***	-0.113	-3.000***	0.089	-7.000***	0.268	-3.000	0.161	3.000	0.348**	-0.028	0.031	-0.025	-0.021
	(0.000)	(1.059)	(0.000)	(0.155)	(0.000)	(0.315)	(0.000)	(0.553)	(.)	(0.188)	(.)	(0.164)	(0.145)	(0.030)	(0.059)	(0.016)
Early	-11.750***	0.761	1.059**	0.087	-3.625***	-0.491	-7.008***	0.170	-2.150***	1.178**	1.152	-1.127	-0.104	-0.150*	0.124*	0.028
	(1.044)	(3.326)	(0.511)	(0.872)	(0.471)	(0.971)	(0.276)	(1.323)	(0.085)	(0.491)	(1.228)	(1.031)	(0.157)	(0.074)	(0.062)	(0.077)
Early*part.	12.500***	0.034	-1.031***	-0.073	3.744***	0.564	7.206***	0.062	2.771***	-0.500	-2.051	0.234	-0.065	-0.011	-0.028	0.064
	(0.587)	(2.146)	(0.310)	(0.425)	(0.257)	(0.497)	(0.314)	(0.878)	(0.094)	(0.502)	(1.369)	(1.090)	(0.151)	(0.044)	(0.069)	(0.049)
With controls																
Participation	-11.010***	0.816	0.719**	-0.209	-2.908***	0.199	-5.918***	0.543	-2.806***	0.246	2.622***	0.201	-0.047	0.004	-0.005	-0.002
	(1.019)	(1.056)	(0.324)	(0.155)	(0.281)	(0.333)	(0.440)	(0.585)	(0.299)	(0.146)	(0.553)	(0.221)	(0.155)	(0.036)	(0.054)	(0.020)
Early	-8.609***	2.957	1.339***	0.516	-2.727***	0.024	-5.608***	0.721	-1.608***	1.860***	-1.305***	-2.813***	-0.068	-0.177***	0.187***	0.032
	(0.727)	(2.512)	(0.216)	(0.730)	(0.187)	(0.841)	(0.417)	(1.153)	(0.190)	(0.244)	(0.420)	(0.433)	(0.150)	(0.058)	(0.047)	(0.066)
Early*part.	10.551***	-0.766	-1.104**	-0.309*	3.213***	0.502	6.143***	-0.067	2.536***	-0.839***	-0.214	1.169***	-0.115	0.001	-0.070	0.089***
	(1.208)	(1.065)	(0.494)	(0.148)	(0.397)	(0.343)	(0.416)	(0.561)	(0.266)	(0.163)	(0.519)	(0.195)	(0.140)	(0.036)	(0.059)	(0.026)
	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number	Binary	Number

Note : Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. FE also has clustered standard errors at preschool levels.

4.7. Discussions:

There are three possible explanations for these results:

1. Actual negative impact: Though it is possible that some indoor facilities made children tired, it is hard to think of the correlation as causal—this contradicts qualitative evidence from the field and psychological and psychiatric theories cannot explain these. Even after seeking advice from psychologists and psychiatrists, we cannot find any possible reason why playing would negatively affect mental health.

2. Reverse causality: From the analysis of the sub-group with outdoor playing experience, we found that the reported negative correlation was concentrated among the parents who regularly prohibit children from playing outside. They may be the ones that wanted to let their children take part in the indoor park programme, and therefore participation may have been positively correlated with stress levels.

3. Upward reporting bias: These measured stress levels are parents' and teachers' perceived stress levels of the children. One possible explanation, therefore, is that parents and teachers have an incentive to misreport the children's health levels more negatively to demonstrate the usefulness of continuing the indoor park programme. Those who participated may know that the implementation of the programme was very costly, and may have wanted to justify the continuation of the programme by reporting that the children have poor psychological health. Or, those who participated realised the programme is beneficial, and may have wanted to demonstrate the need for the programme because they were aware of the possibility that it may not be continued. This explanation would be consistent with the heterogeneity that the positive correlation was found among those who prohibit children from playing outdoors and regularly use indoor facilities. Because parents and teachers may feel that, if they filled out the survey saying that children do not have stress issues the Red Cross may terminate the programme, they may bias their report in the negative direction if they know the benefit of the programme.

5. Conclusion

Given evidence from psychiatry, some anticipate that high stress levels among children in Fukushima may have long-term consequences. Therefore, many post-disaster charities have aimed to alleviate such concerns. This study aimed to identify the extent to which the short-term indoor park programmes can help improve the psychological health of children. Tsutsui *et al*. (2011) had already suggested that the impact of indoor playground may be limited. Unfortunately, no causal statement can be made regarding the direct effectiveness of the programme due to lack of randomization. However, ambiguous and inconsistent coefficients indicate that the programme is unlikely to have had a meaningful impact on the psychological welfare of the children.

This study has two major limitations: lack of randomization (no causal statement) and problems of outcome measurement. Participation is not random with respect to observable characteristics, so it is unlikely to be random with respect to unobservables either. The survey used was one that had originally been intended to observe annual impressions, and most of the responses came in too soon after the programme was implemented.

During the course of the study, it was decided to finish the programme in 2013 as there was not sufficient funding to continue it. As the circumstances of funding and anxiety change rapidly in a post-disaster environment, our findings here may not be applicable in the years after the conclusion of the programme. This research highlights the challenges of establishing external validity in a post-disaster environment where evidence is needed.

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CHAPTER 9

Risk Preference of Managers and Firm Investments in Lao PDR

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While there have been numerous micro-econometric studies on risk and poverty in rural developing economies, there have only been a few studies of business risks arising from volatile input and output prices and weak enforcement of contracts. In this paper, we aim to bridge this gap in the literature by analysing a unique survey and experiment data from textile and garment firms in Lao PDR, collected exclusively for this study. To investigate the role of risk preferences of firm managers on a variety of firm investment decisions, we elicit measures of managers' risk preferences through experiments. We find that firms with risk averse managers are more likely to self-finance investments than to borrow from banks or informal sources, leading to lower overall asset levels. A risk averse firm manger is more likely to face binding "self-inflicted" borrowing constraints on additional investments. However, our results also indicate that risk averse managers invest more in their factories' safety measures against fires and injuries. We also examine the association between risk preferences of managers and adoption of management practices. While the results are not statistically significant, we find that risk tolerant managers are more likely to have adopted better practices and to have achieved employment stability.

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1. Introduction

Studies on developing countries have documented that many medium, small and micro enterprises often fail to implement the optimal level of investments (Kremer, *et al.*, 2013). It would be natural to attribute the observed sub-optimality of investments to firm decision-makers' attitudes toward risk. While there have been numerous micro-econometric studies on risk and poverty in rural developing economies, there have been few empirical studies of business risks arising from volatile input and output prices and weak enforcement of contracts (Fafchamps, 2003). Hardly any studies investigated risk attitudes of firm managers in developing counties. Two exceptions known to us are studies by Kremer *et al.* (2013) and Pattillo and Soderbom (2000), both finding that firms with risk tolerant owners make more investments and grow faster than those with risk averse managers.

In this paper, we aim to fill this gap in the literature by analysing a unique survey and experiment data from textile and garment firms in Lao PDR, collected exclusively for this study. Our analysis has two novelties. First, we examine the nexus between firm managers' risk attitude measures elicited by experiments and a variety of their decisions including choices of financing investments and adoption of different production safety measures. Indeed, in his seminal field experiment, Binswanger (1980) pointed out that risk preference differences are important because policymakers may be able to do something about hindrances to the access of capital, but may be able to do less about the risk attitudes of those whom easier access to capital would help (Cardenas and Carpenter, 2008). We believe we can contribute to the literature by investigating associations between risk preference of managers and a variety of investment decisions that firms make.

Secondly, since the textile and garment sectors are the leading sectors of Lao PDR in generating export revenues and job opportunities, identifying binding constraints on growth in these sectors is critical for designing and implementing better development policies for the country. In this context, it is indispensable to understand individual firm managers' decisions.

To preview our analysis and empirical results, we elicit three measures of risk preference in small and medium garment and textile firms in Vientiane: 1) small-stake price list risk experiment with monetary rewards, 2) hypothetical price-list risk experiment with large stake, and 3) hypothetical real-world risky investment decisions. We first examine how these measures are associated with firm characteristics. We find that the first measure, the small-stake price list experiment with monetary rewards, is correlated significantly with the second measure, the hypothetical question with large-stake, but is not consistent with the third measure, the investment choice question. The third measure, however, seems to be strongly associated with the firm's actual investments in the last year, implying that this measure is not suitable for use as a yardstick of manager's underlying preference.

As the main part of this study, we investigate how risk preference, measured by the experiment with real monetary reward, is associated with various firm investment decisions and performance measures. We find that, to finance investments, firms with risk averse managers tend to use their own assets or retained earnings rather than borrow from banks or informal sources. Moreover, the overall investment amount of firms with risk averse managers tends to be lower than that of firms with risk tolerant managers. However, risk averse managers tend to invest more in factory safety measures such as fire exits and alarms.

We then investigate whether risk preference of managers affects adoption of modern style management practices, workers' turnover rate and firm growth. These investigations are motivated by the fact that, in the study region, 60 percent of the firms in our study pointed to "labour (unstable workforce, frequent turnover, worker shortage)" as one of the main problems (Table 9.A.1). Our estimation finds negative correlation between risk-aversion and adoption of better management practices, although the correlation is not statistically significant. We also find that firms with risk tolerant managers tend to grow faster and achieve lower workers' turnover rates, although these results are not necessarily statistically significant.

The rest of this paper is made up of five sections. In Section 2, we describe our survey, experiments and data set. In Section 3 and 4, we show empirical results on the determinants of risk measures and regression results on various investment decisions, respectively. In Section 5, we present our concluding remarks.

2. Data and Descriptive Statistics

We use data from a survey of textile and garment firms in the Vientiane district of Lao PDR, designed by the authors and carried out from January to April 2014. The survey targeted all existing and known Lao national or Thai investment firms in the textile and garment industries in Vientiane. For constructing the population database, we used association directories provided by the industry associations in the garment and textile sectors. As to the garment sector, we employed the directory of garment firms provided by the Garment Manufacturing Association. Since the directory includes not only the association's members but also non-member small garment firms, typically subcontracting to the larger garment firms, we believe that the directory provides us with reliable information about all garment factories in Vientiane. On the other hand, the directory of textile firms is composed only of the members of the Textile and Handicraft Association and non-member information is missing. To complete the list of textile firms, we collected additional information through the following procedure. First, we visited local government offices in three large sub-districts (villages) in Vientiane, i.e., Chanthabuly, Sikhottabong and Xaythany, to gather information on the locations of textile clusters within each village, with up to three clusters in each village. We then visited the representative of each sub-village, obtaining information on the location of textile firms. This helped us to find an additional 30 textile firms not included in the directory.

Through initial phone calls, we confirmed that 63 textile and 45 garment firms on the list were operational. By the end of April 2014, we had successfully interviewed 43 textile and 35 garment firm managers, achieving a response rate of 72 percent. In the surveys with each firm manager, we employed a set of structured questions, which was carefully designed for this study. The questionnaire is composed of eight main modules: Module A) "firm and plant basics" on basic characteristics of each firm; Module B) "Production, sales, costs, and assets" on basic data of firm operation; Module C) "Export and marketing" on export, subcontract, and marketing; Module D) "Decision makers in production process" on management decision makers; Module E) "management" on management practices; Module F) "Workplace" on workplace environment; Module G) "Opportunities and Constraints" on subjective assessments of the opportunities and constraints faced by each firm; Module H) "Uncertainties for plant." We then undertook experiments and subjective questions to elicit the risk attitude of each firm's manager.

We measured risk preference of managers in three ways. First, we carried out a small-stake price list risk experiment with real monetary rewards by asking that "in this experiment, we want to provide you with a small amount of money. You have two options for receiving this money. Which option do you prefer? Option A) receive \$10 for sure, or Option B) toss a coin, and receive \$40 if the coin is head and receive nothing if the coin is tail." The risk tolerant managers in this experiment are defined as the ones opting for the coin toss, i.e., those who choose Option B. Adopting the von Neumann and Morgenstern axioms of a utility function, we can employ the expected utility maximisation framework. For this experiment, those managers who select Option B should satisfy the following condition: $10^{1-\alpha}<0.5*40^{1-\alpha}$, where α represents the coefficient of relative risk aversion. This inequality is equivalent to the situation where the relative risk aversion coefficient in a constant relative risk aversion (CRRA) utility is greater than 0.5.

Secondly, we conducted hypothetical price-list experiment with large stake to complement the above measure. The question asked was as follows: "If you were to choose between the following two options, which option would you chose? A) receive \$10,000 for sure, B) toss a coin, and receive \$40,000 for sure if the coin is head, and receive nothing if the coin is tail." As before, we defined the risk tolerant dummy for Option B, where the relative risk aversion coefficient is less than 0.5.

Finally, we asked hypothetical questions relevant to real-world risky investment. We first explained that "suppose you have a business opportunity to make an investment. If the business is successful, you receive \$100,000, but if the business is not successful, the investment amount is gone and you receive nothing. We assume that the business has a one in two chance, i.e., a 50 percent probability, of success." Then, we asked that "would you invest if the investment cost is X?" for each X in \$10,000; \$20,000; \$30,000; \$40,000; and \$50,000. The maximum investment cost the respondent is willing to pay for the particular investment opportunity represents the level of risk tolerance. For this intuition, we define the risk tolerance measure from this question by dividing the maximum of X by \$100,000 for normalisation.

In some firms, we could not interview the firm manager but only the general manager or shipping manager, who typically is not responsible for all of the firm's production decisions. As risk measures from these respondents are less likely to be influential than those of the firm managers, we omitted these observations from the sample for analysis. In the final sample, we had 61 responses from firm managers. Fifty-five of these managers were also the owners of the firm and six of them were managers employed by the firm owner.

Our measure on management practices is obtained from a series of closed form questions on adoption of practices often considered to be best practices in the United States and Japan. The questions are mostly the same as the survey in Indian textile firms carried out by Bloom *et al.* (2013) and US Census of Management and Organizational Survey. We asked questions in five areas: monitoring and target, quality control, machine maintenance, information technology usage, and human resources management. We then scored answers for each question and created a standardised score for each area. The overall management score is defined as the average of the scores in all areas.

Descriptive Statistics

Table 9.1 shows descriptive statistics of the main variables. In our data, 59 percent of our respondents are textile factories and the remaining 41 percent are in the garment industry. First, we consider at managers' basic characteristics. Managers are largely well educated, with an average of 11.38 years of education. More than 70 percent of the firm managers are female and average tenure is more than ten years. As to the basic firm characteristics, an average firm owns assets worth USD 29,354, excluding land value, and has an average 49.67 workers. While there is no increasing trend in the number of workers, worker turnover rate has been quite high—according to our data, on average, firms have a 17 percent worker turnover rate per year. In the hypothetical question of financing USD 10,000 investments, 26 percent of firms reported that managers face difficulties trying to finance such an investment.

As we can see from the latter half of Table 9.1, measures of risk tolerance show reasonable variation. About 30 to 40 percent of firms are categorised as risk tolerant according to these measures. The degree of credit constraint is measured by a question: “suppose you receive a new order which requires additional investment of $10,000. Would you have any source to fund this investment?” We created an indicator variable for credit constraint taking the value of one if the manager answered “no source” to this question.

Table 9.1: Descriptive Statistics

	Mean	Standard error	N
Basic characteristics			
Textile firm dummy	0.59	0.50	61
Years of education of manager	11.38	3.68	61
Tenure of manager	10.83	7.42	60
Female manager	0.72	0.45	61
Asset value in USD (excluding land)	29354	67597	61
Employment size	49.67	103.48	61
Employment growth rate	-0.14	0.34	61
Turnover rate	0.17	0.30	59
Credit constraint	0.26	0.44	61
(No source to fund investment of $10,000)			
Risk preference			
Risk tolerant manager (Coin experiment)	0.39	0.49	61
Risk tolerant manger (Coin hypothetical)	0.34	0.48	61
Risk tolerant manager (Investment hypothetical)	0.43	0.23	61

3. Determinants of Risk Measures

In this section, we first examine how the three risk-preference measures are related to each other. Based on a canonical theoretical framework, we simply assume that an answer to the coin toss price-list experiment represents a deep parameter of firm manager's risk preference. We then consider how the deep risk preference, measured by the coin experiment, as well as other firm and individual factors, influence answers to the hypothetical risk questions of the coin toss and the hypothetical real-world investment question.

The first three columns of Table 9.2 show the results of ordinary least squares (OLS) regressions of risk tolerance measure from the hypothetical coin game on experiment measure with real money reward controlling for manager and firm characteristics. All of the coefficients on risk tolerance are highly positive and statistically significant. Inclusion of various firm and manager characteristics influences neither the level nor the significance of the coefficients of risk tolerance. The influence of covariates like manager's gender and tenure are found to be insignificant.

The third to sixth columns of Table 9.2 present the results of using a risk measure based on a hypothetical risky investment choice as a dependent variable. First, risk tolerance deduced from the investment question is positively associated with risk tolerance deduced from the coin game, but the magnitudes of estimated coefficients are small and they tend to be insignificant as we add more control variables. Second, risk measure deduced from the investment question is highly significantly associated with manager's tenure (number of years in the current position). Interpreting this result, it is worthwhile to note that the payoff of risky investment is fixed for every respondent. Therefore, in theory, having more experience and knowledge of how to change the payoff in real investment settings should not affect the choice of investment. This does not, however, eliminate a possibility that more experienced managers know better how to cope with the realised shock. In other words, each manager's response to the investment question might have reflected that manager's past experience of coping with the shocks his/her real business experienced. Third, the last column indicates that preference on riskier investment is positive and significantly (at 10 percent) associated with the actual recent investment (log of investment in over the last year +1). A possible interpretation of this result is that the investment question lets the manager consider how she/he reacted to such investment opportunities in recent years. Another interpretation, of course, is that preference on risky investment affects the real investment decisions. But if this is the case, we should also observe positive association between choice of risky investment and asset as a long-run outcome. We tested this conjecture using the asset data, finding that choices on risky investment are uncorrelated with higher asset level.

Table 9.2: Determinants of Risk Measures based on Hypothetical Questions

OLS	Risk tolerant (hypothetical coin toss game with large stake)			Risk tolerant (hypothetical investment question)		
Risk tolerant manager	0.875***	0.862***	0.855***	0.109*	0.0771	0.0898
(Money reward)	(0.0686)	(0.0751)	(0.0769)	(0.0583)	(0.0590)	(0.0557)
Tenure		-0.00242	-0.00113		0.00957**	0.00836**
		(0.00300)	(0.00250)		(0.00391)	(0.00374)
Female		0.133	0.120		0.0470	0.0363
		(0.0936)	(0.110)		(0.0926)	(0.0889)
Education		0.00281	0.00420		0.00375	0.00953
		(0.00627)	(0.00783)		(0.00801)	(0.00906)
Credit constraint		-0.0328	-0.0254		0.00571	-0.00717
		(0.0690)	(0.0706)		(0.0680)	(0.0660)
Log(investment			-0.0105			0.0155**
Over last year)			(0.0123)			(0.00731)
Log(employment			-0.0260			-0.0132
Last year)			(0.0537)			(0.0299)
N. obs.	61	61	61	61	61	61

Notes: textile dummy and manager's years of education, tenure, and gender are controlled in all regressions. Robust standard errors are shown in parentheses.

4. Risk Preference and Firm Performance

In this section, we report the main results of our econometric analysis. We first estimate the empirical model of manager's risk attitude and choice of investment financing sources. We then show the results of decisions on a variety of investments in equipment, safety measures, management practices, and human resources.

4.1. Financing Investments

In Table 9.3, we show estimated regression results on the determinants of investment financing sources. In this table, dependent variables are dummy variables constructed from the survey question, "Suppose you received a new order, which requires additional investment of $10,000 within a month. Would you have any source to fund this investment, and if so what is the primary source?" The first to the sixth columns of the table show that firms with risk averse managers tend to use own assets or retained earnings to finance new investments instead of borrowing money from bank or informal sources. This indicates that firm manager's risk attitude is significantly related to the choice of investment financing. Presuming that there are natural limitations on self-financing new investments, a risk averse firm manager is more likely to face binding "self-inflicted" borrowing constraints on additional investments. In contrast, the last three columns indicate that having no source is not associated with risk preference of the firm managers, indicating that there is no systematic relationship between a manager's risk attitude and exogenously imposed credit constraints.

Table 9.3: Risk Preference and Investment Sources

OLS	Invest from private asset or retained earning			Invest from bank or informal sources			No source of investment		
Risk adverse manager	0.266*	0.277*	0.280*	-0.329***	-0.315***	-0.316***	0.0630	0.0380	0.0357
	(0.151)	(0.157)	(0.160)	(0.114)	(0.112)	(0.114)	(0.141)	(0.148)	(0.150)
Years of	0.0117	0.0222	0.00354	0.00209	-0.00561	0.000981	-0.0138	-0.0166	-0.00452
education	(0.0198)	(0.0209)	(0.0218)	(0.0120)	(0.0139)	(0.0138)	(0.0170)	(0.0185)	(0.0197)
Years of	-0.00964	-0.00833	-0.0120	0.00860	0.00543	0.00674	0.00103	0.00290	0.00530
experience	(0.0103)	(0.0128)	(0.0111)	(0.00685)	(0.00827)	(0.00829)	(0.00994)	(0.0123)	(0.0111)
Female	0.199	0.209	0.220	-0.0915	-0.130	-0.134	-0.108	-0.0788	-0.0863
	(0.181)	(0.191)	(0.185)	(0.150)	(0.152)	(0.152)	(0.167)	(0.162)	(0.165)
Family owned	-0.123	-0.0912	-0.0474	0.189	0.0187	0.00328	-0.0651	0.0725	0.0442
	(0.261)	(0.300)	(0.282)	(0.208)	(0.248)	(0.237)	(0.178)	(0.220)	(0.239)
Textile dummy	0.213	0.142	0.223	-0.426***	-0.379***	-0.408***	0.213	0.237	0.184
	(0.162)	(0.184)	(0.168)	(0.119)	(0.136)	(0.135)	(0.165)	(0.170)	(0.163)
Thai investment	0.304	0.284	-0.0128	-0.477***	-0.806***	-0.701***	0.173	0.521	0.714**
	(0.293)	(0.428)	(0.406)	(0.158)	(0.197)	(0.202)	(0.309)	(0.325)	(0.328)
Log employment			0.141*			-0.0497			-0.0910
			(0.0782)			(0.0537)			(0.0813)
District FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
N. obs.	61	61	61	61	61	61	61	61	61

Notes: Risk adverse is measured as 1- risk tolerant using an experiment with monetary reward. Dependent variables are dummy variables constructed from an answer to a question "Suppose you received a new order, which requires additional investment of $10,000 within a month. Would you have any source to fund this investment, and if so what is the primary source?". Robust standard errors are shown in parentheses.

4.2. Firm Investments

In terms of the amount of investment, firms with risk averse managers tend to invest less in equipment, as shown in Table 9.4. Yet, the standard errors are large, making these estimated coefficients statistically insignificant. Since differential impacts of risk preference are expected by industry and type of equipment, i.e., textile firms using weaving machines and garment firms using sewing machines, we separately estimate the coefficients of risk aversion by industry. The results are reported in the third and fourth columns of Table 9.4. According to the results, an influence of risk aversion tends to be more negative and significant in the textile industry than that in the garment sector.

Contrary to the results on the general equipment investment, firms with risk averse managers tend to invest more on fire safety measures. In the fourth to eighth columns of Table 9.5, we show empirical results with the number of fire safety measures as the dependent variable. For example, this safety measure takes on five when the firm has fire exits, fire hoses, fire alarms, and route maps, and practices fire drills. The estimated coefficient implies that risk averse firm managers tend to have 0.23 more fire safety measures compared with their risk-tolerant counterparts. Moreover, in the last specification, we can see that this risk aversion effect on safety measures is strong in the textile industry.

Table 9.4: Risk Preference and Investment on Equipment and Fire Safety Measures

OLS	Log (value of equipment)				Number of fire safety measures			
Risk adverse manager	-0.391	-0.378			0.231	0.234*		
	(0.422)	(0.278)			(0.145)	(0.139)		
Risk adverse manager			-0.646*	-0.495			0.246	0.328*
x Textile			(0.379)	(0.393)			(0.150)	(0.164)
Risk adverse manager			0.0626	0.0757			0.214	0.171
x Garment			(0.422)	(0.459)			(0.273)	(0.249)
Years of	0.160***	0.0324	0.0392	0.0347	0.0534**	0.0221	0.0217	0.00941
education	(0.0502)	(0.0460)	(0.0491)	(0.0519)	(0.0241)	(0.0287)	(0.0284)	(0.0258)
Years of	0.0645	0.0430*	0.0389*	0.0391	0.0139	0.00859	0.00878	-0.00195
experience	(0.0409)	(0.0228)	(0.0230)	(0.0283)	(0.0125)	(0.00927)	(0.00969)	(0.0126)
Female	-0.321	-0.206	-0.173	-0.318	0.658***	0.687***	0.685***	0.626**
	(0.491)	(0.330)	(0.338)	(0.342)	(0.244)	(0.244)	(0.245)	(0.234)
Family owned	-0.691	-0.292	-0.510	-0.985	-0.0812	0.0173	0.0271	-0.0863
	(0.868)	(0.642)	(0.644)	(0.670)	(0.487)	(0.472)	(0.466)	(0.333)
Textile dummy	-1.830***	-1.249***	-0.826	-0.831	-1.308***	-1.165***	-1.184***	-1.031***
	(0.443)	(0.334)	(0.587)	(0.616)	(0.222)	(0.245)	(0.308)	(0.283)
Thai investment	1.862**	-0.212	-0.266	-0.740	1.844*	1.332	1.335	0.916
	(0.741)	(0.529)	(0.515)	(0.760)	(0.993)	(0.969)	(0.982)	(0.871)
Log employment		1.003***	0.976***	0.976***		0.247**	0.248**	0.243***
		(0.147)	(0.143)	(0.154)		(0.110)	(0.108)	(0.0833)
District FE	No	No	No	Yes	No	No	No	Yes
N. obs.	61	61	61	61	61	61	61	61

Notes: Risk adverse is measured as 1- risk tolerant using an experiment with monetary reward. Robust standard errors are shown in parentheses.

4.3. Management Practices

We then analyse the association of risk preference and firm management practices, turnover rate, and employment growth. As shown in Table 9.5, although all of the coefficients of risk aversion are insignificant, we still see some qualitative patterns that are worth investigating in future research. On firm management practices, the results indicate that risk averse managers are less likely to have adopted modern style management practices. This could be a result of the fact that the adoption of new practices requires trial and error, which can be regarded as risky investment.

As evident from the fourth to the last column of Table 9.5, risk averse managers are more likely to be suffering from a high turnover rate and lower employment growth. While their estimated coefficients are statistically insignificant, these qualitative features might be related to the lower rate of adoption of better management practices among the risk averse firm managers, which generates constraints in employing and retaining workers.

Table 9.5: Risk Preference, Management Practices, Turnover, and Firm Growth

OLS	Management score			Worker turnover rate			Employment growth		
Risk adverse manager	-0.110	-0.103	-0.106	0.0941	0.0825	0.0775	-0.110	-0.108	-0.118
	(0.256)	(0.202)	(0.224)	(0.0900)	(0.0799)	(0.0855)	(0.114)	(0.106)	(0.113)
Years of education	0.0966**	0.0319	0.0179	-0.00588	0.00486	0.0110	0.00223	-0.0126	-0.0154
	(0.0368)	(0.0339)	(0.0362)	(0.00752)	(0.0121)	(0.0147)	(0.0116)	(0.0140)	(0.0146)
Years of experience	-0.00227	-0.0132	-0.0216	-0.00103	8.64e-05	0.00167	-0.00377	-0.00628	-0.00811
	(0.0191)	(0.0112)	(0.0140)	(0.00931)	(0.00811)	(0.00904)	(0.00770)	(0.00631)	(0.00815)
Female	-0.306	-0.248	-0.270	0.0770	0.0519	0.0655	0.226*	0.239*	0.249*
	(0.331)	(0.224)	(0.231)	(0.0785)	(0.0584)	(0.0615)	(0.123)	(0.124)	(0.140)
Family owned	-0.955**	-0.751**	-0.771	-0.0485	-0.114	-0.0730	0.208	0.255**	0.288*
	(0.390)	(0.358)	(0.484)	(0.0866)	(0.0986)	(0.112)	(0.129)	(0.114)	(0.171)
Textile dummy	-0.207	0.0883	0.176	0.0935	0.0641	0.0527	-0.0647	0.00293	0.0327
	(0.326)	(0.232)	(0.229)	(0.0866)	(0.0828)	(0.0815)	(0.118)	(0.134)	(0.142)
Thai investment	0.117	-0.939**	-0.947*	-0.0155	0.212	0.356	0.269	0.0276	-0.0135

	(0.511)	(0.419)	(0.485)	(0.0698)	(0.177)	(0.239)	(0.187)	(0.199)	(0.201)
Log employment		0.511***	0.519***		-0.0837	-0.0941		0.117*	0.117*
		(0.121)	(0.112)		(0.0648)	(0.0652)		(0.0602)	(0.0607)
District FE	No	No	Yes	No	No	Yes	No	No	Yes
N. obs.	61	61	61	59	59	59	61	61	61

Notes: Risk adverse is measured as 1- risk tolerant using an experiment with monetary reward. Robust standard errors are shown in parentheses.

5. Concluding Remarks

While previous studies have shown firm managers' risk preferences matter for investment in physical assets, the effect of managers' risk attitudes to the adoption of broader investments and management practices were largely unknown. In this study we aim to fill this gap in the literature by employing measures of management practices as well as a variety of measures of risk preference in Lao firms.

Testing for consistency among risk measures, we first found that answers to hypothetical investment questions are only weakly associated with risk preference measured from the coin toss game with real monetary reward and largely influenced by managers' tenure and recent investment cases. It is likely that, when firm managers are asked about choices on risky investment, they think back to how they behaved in such situations in recent years. Therefore, we decided to mainly use risk measures from experiments in the regression analysis.

We subsequently found that risk averse firms are more likely to use own assets and retained earnings to fund investments, rather than trying to obtain credit from banks or informal sources. These results suggest that, for risk averse managers, binding credit constraints for various investments arise not from a lack of access to credit markets but from self-inflicted borrowing constraints. This finding postulates a difficult policy question since policymakers can relax credit constraints by improving access to capital but may be able to do less about the self-inflicted credit constraints arising from risk aversion (Binswanger, 1980; Cardenas and Carpenter, 2008).

Our results also indicate that risk averse firms are equipped with lower levels of machinery capital, but with higher levels of fire safety measures. We also looked at how risk preference is associated with firm management practice and employment stability. While the results are not statistically significant, we found that risk tolerant firms tend to adopt better management practices, to increase employee numbers and achieve lower employee turnover rates.

Since the textile and garment sectors are Lao PDR's leading sectors in terms of generating export revenues and jobs, identifying binding constraints on growth in these sectors is critical for designing and implementing better development policies for the country. We believe the results of our studies have important policy implications in terms of the light they shed on individual firm managers' decisions. But our paper has an important caveat—the small number of observations. Because of the lack of statistical power, we cannot draw firm conclusions as to the statistical significance of the estimated parameters. This calls for future research to collect more data for a better understanding of the validity of risk measures.

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Appendix

Table 9.A.1. Source of the Most Significant Uncertainty for Profit

	Percentage
Weather (seasonality, rainfall, temperature, and etc.)	27.87
Labor situation (frequent worker turnover, unstable workforce, and etc.)	24.59
Foreign exchange rate	13.11
Consumer preference (change in trend, and etc.)	6.56
Government economic policies (tax, subsidies, regulations, and etc.)	8.2
Trade policies (licensing, tariff, and etc.)	1.64
Other	18.04